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The Impact of Pandemic Shocks to the Stock Market

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Abstract

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Key words: Stock Market, Volatility, COVID-19, Pandemic Shocks, GARCH, TGARCH

Purpose: The purpose of this thesis is to analyze how the financial services sector in North America is affected by pandemic shocks in the 21st century by estimating the volatility in the stock market.

Methodology: Firstly, the effect of the COVID-19 shock on the market volatility of the financial services sector was examined. Secondly, a comparison of the magnitudes of the effect on the other known shocks was performed. Lastly, a comparison between the financial services sector and the diverse sectors was conducted.

Theoretical perspective: A classical ARCH (1,1) model and a GARCH (1,1) model were implemented to assess market volatility, and a TGARCH (1,1) model was executed to estimate its asymmetrical effects of positive and negative returns.

Empirical Foundation: The study conducted two samples of data. One sample consisted of thirty financial services companies in North America that were active from 1st August 2002 to 8th May 2020. Meanwhile, the second sample examined the volatility of thirty blue-chip companies from diverse sectors recorded in the Dow Jones Industrial Average index.

Conclusions: The main findings indicate that the financial services sector responds less severely to pandemic shocks compared to other known shocks on the market. Furthermore, the results indicate that the leverage effect is not observed during pandemic outbreaks.

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1. Introduction

In the introduction section, a brief background of the chosen topic will be presented. This will be followed by a motivation for the study. Later on, the determined purpose, research question, and the hypothesis of the thesis will be described. This section will be completed by presenting the limitations in the study and describing the structure of this paper.

1.1 Background & Motivation

The outbreak of the Coronavirus disease (COVID-19) has shaken the world in various ways. One of the most affected actors by this pandemic shock is the stock market. This ongoing event, which began on 20 February 2020 is known as the stock market crash of the year 2020. (The Guardian, 2020; The Washington Post, 2020). COVID-19 has made an impact on the stock market, due to its dramatic fall in the stock market prices. This pandemic, for instance, has been one of the reasons for the causes of equities plummeted, oil price war, and market volatility all around the world (BBC News, 2020). In the U.S., the S&P 500 index fell where the closing S&P 500 price was $3 321 on 21th January 2020. All of sudden, on 23rd March 2020, the S&P 500 price fell around 30% and reached $2 237 (Reuters, 2020). This result showed that the pandemic outbreak had severely affected the S&P 500 index.

In the 21st century, the *World Health Organization* (WHO) has so far declared the COVID-19 and the swine flu pandemic (known as H1N1) as pandemics for this period (World Health Organization, 2020a; 2020b). WHO defines a pandemic as a new influenza virus that develops and spreads around the world, where most people do not have immunity against the virus (World Health Organization, 2010). Baker, Bloom, Kost, Sammon & Viratyosin (2020) studied the stock market's reaction to COVID-19. The authors compared it with a century earlier pandemic, known as The Spanish Flu, which had not impacted the stock market as much as the part of the COVID-19 outbreak has caused. Baker et al. (2020) also found that infectious disease outbreaks did not have a huge presence on the stock market from 1985 until the COVID-19 pandemic outbreak spread throughout the world and affected the stock market from 24 February 2020.

The stock market can be triggered by other known shocks. The energy crisis is one example of such a known shock. Studies have been conducted where they could agree that an increased price in energy is a potential contributor to an impact on the stock market (Alpanda & Peralta-

Alva, 2010; Wei, 2003). However, to our knowledge, studies have not been conducted regarding the comparison of how the energy crisis in the 2000s has affected the stock market.

Another known shock is the Chinese stock market crisis in 2015. Chen and Gong (2019) conducted a study regarding this event due to its increased influence on the factors that determine the volatility of stock spot and future markets. This event was also a concern for the U.S. stock market (U.S.–China Economic and Security Review Commission 2016; 2017). Several studies have been performed regarding the relationship between the stock market and various economic shocks. Some of the studies were conducted by estimating the volatility in the stock market (Ederington & Guan, 2010; Degiannakis, Filis & Kizys, 2014; Kang, Ratti & Yoon, 2015). There are many documented shifts in the volatility of the historical stock returns. These shifts may be caused by positive and negative shocks that affect different sectors (Dendramis, Kapetanios & Tzavalis, 2015).

The topic of this paper is a relevant theme since the COVID-19 pandemic hit the world at the end of 2019 and is still considered as an ongoing event (World Health Organization, 2020c). Therefore, it is important to analyze how great of an impact COVID-19 outbreak has on the stock market. Since volatility is most used when examining the reaction on the stock market, volatility can also depend on which sector is examined in the stock market. One of the most volatile sectors is the financial services sector. This sector includes companies that operate in financial services, banks, credit card issuers, brokerage firms, insurance, commodity, and securities exchanges. During the financial crisis 2007–2008 and the Great Recession that followed the financial crisis, this sector experienced tremendous volatility (Chan-Lau, Liu & Schmittmann, 2015; Hodges & Lapsley, 2016).

Although several studies have examined the relationship between the stock market and other shocks, there are exceptionally limited studies concerning the relationship between the stock market and pandemic shocks, which is applied in the financial services sector. In addition, studies regarding pandemic shocks have a bigger or smaller impact compared to the other known shocks on the stock market is also limited. Furthermore, a review of the literature on this topic found that the number of empirical papers on COVID-19 is still limited (Sansa, 2020).

1.2 Thesis Purpose, Research Question & Hypothesis

The purpose of this thesis is to analyze how the financial services sector in North America is affected by pandemic shocks in the 21st century by estimating the volatility in the stock market. This result will be compared and examined to other known shocks to analyze how big of an impact the pandemic shocks have on the financial services sector in the stock market. Thus, the main aim of this paper is to analyze how big of an impact the pandemic shocks have compared to other known shocks in the financial services sector in the stock market.

The research question is:

- Does the financial services sector react more or less severely to pandemic shocks compared to other known shocks to the market?

The hypothesis based on the research question:

- Pandemic shocks have lower volatility than other known shocks.

1.3 Limitations of the Study

The sudden fall in the S&P 500 price in March 2020 resulted in the S&P 500 index being severely affected by the COVID-19 pandemic outbreak. In addition, due to financial services sector's tremendous volatility during financial crisis and the great Recession, this paper is determined to focus on the impact of pandemic shocks in financial services sector in North America. We use the *North American Industry Classification System* (NAICS) Code to identify the financial services companies, where NAICS covers businesses that are active in Canada, Mexico, and The United States. In the category of financial services companies, it includes businesses that are active in Finance or Insurance. The study is also limited to pandemic shocks that has been declared by the *World Health Organization* (WHO). Epidemic shocks tend to have a smaller impact and tend to show effects on the concerned country rather than globally, which would not be relevant for the research question where it considers the whole North American industry. In addition, the paper is restricted to events that occurred in the 21st century due to investigating the pandemic shocks compared to modern other known shocks.

1.4 Thesis Structure

The first section describes a brief background of the chosen topic and states the main motivation and purpose of this thesis. This is followed by the thesis's research question and hypothesis as well as the limitations that have been done for the study. The following section characterizes the theoretical background of volatility and models used to estimate and to analyze asymmetric volatility. The next section presents the literature review of the current knowledge of the topic. Further on, the data description and methodology are outlined in the fourth and fifth sections. At a later point, the main findings will be reported in the sixth section. The interpretation and discussion of the main findings and a discussion with the literature review section will be presented in the following section. Lastly, the paper will draw the following conclusions of the report and suggest possible further research.

2. Theoretical Framework

In this chapter, the paper will present different models that are commonly used when estimating volatility in stock prices. This will be followed by introducing simple statistical measures of volatility and then discuss more complicated econometrics models such as the GARCH model and its variances.

2.1 The Relationship Between Volatility & Shocks

Daly (2019) states that prices set in the stock market both assess the actual cost of new capital for firms that issue shares and provide a measure of the opportunity cost of capital that is acquired through retained earnings. First, prices set can be referred to as being efficient by incorporating all available relevant information in the market. Second, he argues that the market is efficient if the markets manage to reflect all relevant information in forming expectations that determine fundamental values. Finally, he further explains that where markets do achieve market efficiency, large changes in stock prices tend to reflect the large shifts in investors' rational expectations about the future values of the fundamental economic variables, which in return impacts the valuation of common stocks. Thus, he concludes that the presence of irrational investors' behavior or near-rational bubbles in the stock market is possible reason for the economists' inability to explain stock market volatility. However, he believes that if the markets are inefficient, traders tend to act to earn excess profits based on other information. Daly (2019) also introduces three authors that noted that changes in expectations regarding the interest rates, perceived risk premium and future dividend could affect stock prices, and because expectations are conditional upon the available information, new information about these variables may affect price volatility. This new information can be perceived as a shock to the traders and the stock market (Daly 2019). Thus, it is important to know for how long the shocks persist over time, which can be estimated with volatility.

2.2 Types of Volatility

Volatility is an important concept in finance. It is often used as a crude measure of the total risk of financial assets and is measured by the standard deviation or the variance of the asset returns. There are various models that one uses to capture the stylized features of volatility (Brooks, 2014). Forecast and volatility are highly related due to a good forecast of the volatility of asset prices over the investment holding period, which is a good starting point for assessing investment risk (Poon & Granger, 2003). The most used volatility measures are realized volatility, implied volatility, conditional volatility, and unconditional volatility.

2.2.1 Framework of Realized Volatility

Realized volatility, which can sometimes be referred to as historical volatility, has the simplest model for estimating historical periods for volatility. Realized volatility involves calculating the variance of returns over historical periods. This results in becoming the volatility forecast for all future periods. However, there are empirical studies that suggest realized volatility is now more useful as a benchmark for comparing the forecasting ability of more complex time models (Brooks, 2014). The empirical studies also suggest that the use of predicted volatility from more sophisticated time series models will lead to more accurate options valuations (Akgiray 1989; Chu & Freund, 1996).

2.2.2 Framework of Implied Volatility

Implied volatility is the expected volatility in a stock's return derived from, for example, its option date maturity date, a risk-free interest rate, the exercise price by using an option-pricing model (the standard Black-Scholes model) (Nasdaq, 2020). In Christensen and Prabhala's (1998) study, they found that implied volatility outperforms realized volatility in forecasting future volatility due to their longer time series and nonoverlapping data in the study.

2.2.3 Framework of Unconditional & Conditional Volatility

Forecasting volatility can be divided into two categories: *unconditional volatility* and *conditional volatility*. Unconditional volatility can be expressed as a mean of the volatility for an observed period. The approach can be simply explained as if the preceding return is not explicitly observed, it is possible to determine the next day's volatility by the mean for the entire period (Hayashi, 2000). However, models for unconditional volatility do not consider volatility clustering (Brooks, 2014). Volatility clustering illustrates the tendency of large changes, of either sign, tend to be followed by large changes, and small changes, of either sign, tend to follow small changes (Mandelbrot, 1967). The approach is straightforward by the current level of volatility tends to be positively correlated with the level during its immediately preceding periods. Thus, the conditional forecast is a better method for this analysis. Conditional volatility incorporates all information that is available at each time period. In other words, the conditional forecast approach can be applied if the volatility can be observed for each time period (Hayashi, 2000; Brooks, 2014). Therefore, the most well-known models to more accurately describe the phenomenon, volatility clustering, and the use for forecasting conditional variance are the ARCH (Engle, 1982) and GARCH (Bollerslev, 1986) models (Hayashi, 2000; Brooks, 2014).

2.3 Simple Measurements of Volatility

Andersen, Davis, Kreiß and Mikosch (2009) describe one way of estimating the volatility simply is measuring *the average volatility over a given period*. Simply put, volatility is the squared root of the variance of the returns. The variance can be estimated with the following formula (Andersen et al., 2009):

$$\widehat{\sigma}^2 = \widehat{Var\,(r)} = \frac{1}{T}\sum_{t=1}^{T}(r_t - \bar{r})^2$$

Where r_t: the return in period *t*. If r_t are daily returns, this will give an estimate of daily volatility. $\bar{r}$ = $\widehat{\frac{1}{T}}\sum_{t=1}^{T} r_t$ is the sample mean and *T* is the number of observations.

Another way of estimating the volatility is relying on "historical" volatility measures using a *backward-looking rolling sample* to estimate volatility. Andersen et al. (2009) conclude that if the gathered data is daily, it is possible to compute the volatility for each month or year in the sample. This will be considered as daily volatility. However, they believe that the hindrance of using the rolling sample estimates is conditionally biased given the history of the past returns are used due to volatility is persistent but also clearly mean-reverting, which emplaces that this unit root type forecasts of future volatility is not the most optimal option. For instance, if we have monthly estimates of volatility, there is no real guidance of how they connect nor how they could form as a useful forecast. They conclude that the method does not get an estimate of the "current" volatility, which means it does not deliver a spot estimate of today's nor yesterday's volatility (Andersen et al., 2009).

2.4 ARCH Model

To consider volatility clustering, Engle (1982) introduced the *Autoregressive Conditional Heteroscedasticity* (ARCH) model. It is sensible and recommended to first estimate this model to make sure that a GARCH-type model is appropriate for the data (Brooks, 2014).

The general case of estimating the ARCH(q) model is where the error variance is dependent on the lags (q) of squared errors (Brooks, 2014):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mathrm{u}_{t-1}^2 + \alpha_2 \mathrm{u}_{t-2}^2 + \cdots + \alpha_\mathrm{q} \mathrm{u}_{t-\mathrm{q}}^2$$

where α_0 has to be larger than. $0\sigma_t^2$ is where conditional variance at time t, whereas α_0 is the volatility of the beginning of the period. $\alpha_1 \mathrm{u}_{t-1}^2$is a volatility during the previous period, where u_t is an error (an innovation term). q is interpreted as the number of lags.

The conditional variance for ARCH (q):

$$\sigma_t^2 = \mathrm{Var}(\mathrm{u}_t|\Omega_{t-1}) = \mathrm{E}[\mathrm{u}_\mathrm{t}^2|\Omega_{t-1}]$$

where Ω is known as the information set.

The unconditional variance for ARCH (q):

$$\sigma^2 = \frac{\alpha_0}{1 - \alpha_1 - \alpha_2 - \cdots - \alpha_\mathrm{q}}$$

In the context of homoscedasticity, the unconditional variance is equal to the conditional variance (Hayashi, 2000).

However, the ARCH(q) models have limitations. One issue is how the value of q, the number of lags of the squared residual in the model should be determined. Another issue is that non-negativity constraints might be violated, where more parameters involved in the conditional variance equation can lead to one or more of them will have negative estimated values. Yet another issue is the value of q, the number of lags of the squared error might be very large, which can lead to a large conditional variance model that is not parsimonious. Thus, the ARCH model is not widely used as before. Instead, the developed version of the ARCH model, GARCH model, is a more common model for estimating volatility in modern studies.

2.5 GARCH Model

The well-known model for conditional volatility is the improved version of the ARCH model, *Generalized ARCH* (GARCH) model that was developed by Bollerslev (1986). GARCH comes from the original time series model and is a more preferably and widely used model in practice compared to ARCH due to the ARCH(q) model's limitations. GARCH is less likely to breach non-negativity constraints and is considered as more parsimonious and avoids overfitting. The model also allows an infinite number of past squared errors to influence the current con (Brooks, 2014). The GARCH model gives the possibility of the conditional variance to be dependent upon previous own lags. This model is also known as conditional variance due to its one-period ahead estimate for the variance calculated based on any past information thought relevant.

The GARCH (1,1) model is considered as a parsimonious model, that allows an infinite number of past squared errors to affect the current conditional variance. However, the GARCH (1,1) model can be extended to the GARCH (p,q) formulation. This allows the current conditional variance is parameterized to depend upon q lags of the squared error and p lags of the conditional variance (Bollerslev, 1986):

$$\sigma_t^2 = \propto_0 + \sum_{\mathrm{i}=1}^{\mathrm{q}} \propto_{\mathrm{i}} \mathrm{u}_{t-\mathrm{i}}^2 + \sum_{\mathrm{j}=1}^{\mathrm{p}} \beta_{\mathrm{j}} \sigma_{t-\mathrm{j}}^2$$

where p has to be larger or equal to 0 and q has to be larger than 0. $\propto_0$ also has to be larger than 0, whilst $\propto_{\mathrm{i}}$ can be either larger or equal to 0. The variable, β, is a vector of unknown parameters

In general, the GARCH (1,1) model is considered as sufficient enough to estimate the volatility clustering in the data (Books, 2014).

In conclusion, the main advantage of using the GARCH model rather than the ARCH model is the GARCH model integrates the preceding forecasted variance, and the model simply applies fewer parameters. This results in reducing the likelihood of violating the non-negativity constraints (Campbell et al, 1998). Nonetheless, either the GARCH model or ARCH model provides the possibility to incorporate the asymmetric volatility. With the GARCH model as a foundation, two asymmetrical formulations have been developed (Hayashi, 2000; Brooks, 2014). Brooks (2014) mentions one asymmetrical model that is widely used: The exponential GARCH (EGARCH) model that was introduced by Nelson (1991). Lastly, the threshold GARCH (TGARCH) will be discussed, where these two models also come from the original time series model.

2.6 EGARCH Model

The *exponential GARCH* model was developed by Nelson (1991). There are empirical studies that state EGARCH outperforms other conventional GARCH models such as the GJR-GARCH model regarding its reflection of the returns in terms of serial correlation, asymmetric volatility clustering, and leptokurtic innovation (Alberg, Shalit, & Yosef, 2008). In other words, stating that the EGARCH model yields a more accurate and adequate result.

The conditional variance equation of the EGARCH model can be expressed in various ways, this is one possible specification given by Brooks (2014):

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{\lceil u_{t-1} \rceil}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]$$

where ω is the intercept, β is the coefficient for the term of the logged GARCH, $\ln(\sigma_{t-1}^2)$ is the term of the logged GARCH, γ is the proportion of the asymmetric volatility, where $\gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}}$ is the standardized last period's shock and $\left[\frac{\lceil u_{t-1} \rceil}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]$ is the absolute value of the volatility shock of the last period.

The variable γ states the size of the asymmetric volatility and whether it is positive or negative (Nelson, 1991).

if:

$\gamma > 0$, the positive shocks are the ones that will increase the volatility rather than the negative shocks.

$\gamma < 0$, the negative shocks are the ones that will increase the volatility rather than the positive shocks.

$\gamma = 0$, no asymmetric volatility exists.

As stated in Glosten, Ravi and Runkle (1993) study, the standard EGARCH-M model does not manage to capture the time-series properties of the monthly excess return on stocks, where a more general specification is needed in this model. Ultimately, Glosten et al (1993) found a negative relation between conditional variance of monthly return and conditional expected monthly return.

2.7 TGARCH Model

The *threshold GARCH* (TGARCH) model was presented by Zakoian (1994). Compared to the EGARCH model, which also models asymmetries in volatility, the TGARCH model does not square the positive and negative parts of the noise. It rather specifies the conditional standard deviation instead of the conditional variance. Zakoian (1994) also states that the TGARCH model provides additive modeling and makes volatility a function of nonnormalized innovation, which the EGARCH model does not. Accordingly, the TGARCH model preserves the future of the classical GARCH models.

The TGARCH model (*p,q*) process for the conditional variance is given by (Zakoian, 1994):

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

where the variable, γ, is the asymmetry or leverage parameter.

if:
$\varepsilon_{t-1} < 0$: bad news, which has an impact on $\alpha_i + \gamma_i$.
$\varepsilon_{t-1} > 0$: good news, which has an impact on α_i.
$\gamma \geq 0$: negative shocks have a larger effect on σ_t^2 than positive shocks.

With this explained, the TGARCH model imposes different lags which may yield opposite contributions as far as asymmetry is concerned, whilst the EGARCH model imposes a constant structure at all lags. Thus, this thesis will use the GARCH (1,1) model and the TGARCH (1,1) model.

3. Literature Review

The literature review section is divided as followed. First of all, studies that have analyzed the various types of economic shocks to the stock market will be presented. This will be followed by what type of models have been most frequently used to estimate the stock market volatility in the respective studies. This section is concluded with a summary of the gathered literature.

3.1 Economic Shocks to Stock Market

There are various types of economic shocks that are analyzed. Economic shocks are unpredictable phenomena, which can influence economic performances (Lütkepohl, 2008). Thus, pandemic shocks related to the volatility in the stock market has become more relevant to analyze in this period, which has a limited area of research (Sansa, 2020) In addition, studies that have examined the stock price behavior and changes in the volatility during pandemic shocks in the financial services sector is also limited.

On the contrary, there have been studies regarding the relationship between the stock market and other known shocks by estimating stock market volatility. Simply put, several studies have looked at the issue of returns and volatility transmission between other known shocks and stock returns at both the market level and sector level. Charles and Darne (2014) analyzed whether the rare events such as major financial crises, macroeconomic news, declarations on the economic situation, and bankruptcy were the causes to large volatility shocks. The study estimated the stock market volatility with data from high frequencies. The sample of this data consisted of thirty companies that were listed in the Dow Jones Industrial Average, which is a stock market index in the United States. The authors could conclude that these mentioned large shocks are principally the cause to large volatility shocks. As mentioned briefly earlier, the U.S.–China Economic and Security Review Commission (2016; 2017) has conducted studies regarding the U.S. financial exposure to China and how China's stock market meltdown has shaken the world due to the China Stock Market crisis in 2015. The impact of China's slowing growth and economic reforms has the tendency of affecting the global financial markets, including the U.S. financial markets (U.S.–China Economic and Security Review Commission, 2017).

In terms of oil price shocks, Degiannakis, Filis, and Kizys (2014) analyzed the effect of oil price shock whereas such an event has a smaller influence on the stock market returns in the short term. In their study, the gathered data was converted from the daily volatility into the monthly volatility in order to differentiate between various types of volatilities at different frequencies. Degiannakis et al. (2014) found, as a result, that the oil price changes due to aggregate demand shocks lead to a reduction in stock market volatility. Similarly, Arouri and Rault (2012) found that there is a long-run link between oil price shocks and stock market returns in the Gulf Cooperation Council (GCC) countries. In addition, Arouri and Rault (2012) also encourage that GCC countries, this long-run link, can vary from one economic industry to another. Simply put, sector analysis of this long-run link would be, as Aruori and Rault (2012) assert, informative if an investigation of asymmetric reactions of sector indices to price changes was performed. In contrast, Aloui and Jammazi (2010) who also conducted a study regarding the oil price changes and stock market returns for the UK, France, and Japan, did not find any particular relationship after the 1999 period (except for Japan). The oil price changes but does not affect the recession stock market phases, instead, the oil price changes reduce moderate and/or expansion stock market phases momentarily (Aloui & Jammazi, 2010). Aloui and Jammazi (2010) also state that the advancement of technology may also be a reason for the reduced impact of the oil shock, for instance, by reducing the dependency on oil. This study also proves that there is a relationship between oil price shocks and stock market in various countries.

3.2 Models for Estimation of Volatility

There are different models that can be used to explain the relationship between economic shocks and stock market volatility. For instance, Sakata and White (1998) used the ARCH model in their research. However, this model was deemed as not as sufficient anymore and was later replaced by the developed model of the ARCH model, the GARCH model, which is the most widely used model when estimating volatility. Furthermore, Day and Lewis (1992) examined the information content of the ex-ante estimates of future market volatility implicit in the prices of call options on both the Standard and Poor's 100 index. The authors used the GARCH model in hope of the model may be useful in predicting future volatility. Day and Lewis (1992) could also draw the conclusion that, in certain instances, the GARCH model provided better forecasts than the EGARCH model. In addition, Agnolucci (2009) used the GARCH model to compare it with the implied volatility method regarding crude oil in the energy sector. The author came to the conclusion that the GARCH-type models outperformed the implied volatility method (Agnolucci, 2009).

Kang, Kang, and Yoon (2009) investigated the efficacy of a volatility model for three crude oil markets. Kang et al. (2009) wanted to examine the ability of a volatility model to forecast and identify volatility persistence or long memory. The authors used the GARCH model (also known as the linear GARCH model) and the GARCH-class models that consider the asymmetric volatility (also known as the nonlinear GARCH-class models). Kang et al. (2009) could conclude that the nonlinear GARCH-class models outperformed the linear GARCH model as being more useful for modeling and forecasting persistence in the volatility of crude oil prices. Accordingly, Wei, Wang, and Huang (2010) decided to conduct a study of having Kang et al. (2009) as the base to further prove the evidence of the use of GARCH models. Wei et al. (2010) decided to use a greater number of the linear GARCH-class model and the nonlinear GARCH-class models to capture the volatility features of two crude oil markets and to further prove the point of Kang et al (2009) research. On the contrary to Kang et al. (2009), Wei et al (2010) could not find any models that could outperform all of the other models for the two crude oil markets. However, the conclusion of Kang et al (2009) remain. The nonlinear GARCH-class models outshined the linear GARCH-class model by being more capable of capturing long-memory and/or asymmetric volatility and demonstrating greater forecasting accuracy than the linear GARCH-class model, and especially in forecasting volatility over a longer time horizon.

Awartani and Corradi (2005) drew an interesting conclusion in their study. The authors wanted to examine the relative out of sample predictive ability of the various GARCH models, with a particular emphasis on the predictive content of the asymmetric component. The conclusion was that the GARCH (1,1) model was outperformed by the asymmetrical GARCH models in the case of a one-step-ahead pairwise comparison. However, the GARCH (1,1) model outperforms other GARCH models that do not allow for asymmetries (Awartani & Corradi, 2005). This indicates that relying entirely on the GARCH (1,1) model when analyzing the stock market volatility will not be enough. Hence, adding another GARCH model which considers the asymmetric volatility is necessary. The aim of the TGARCH models is to analyze the asymmetrical effect of the returns. Sun and Yu (2019) used the TGARCH model to extend it to a functional TGARCH (fTGARCH) model in regard to asymmetric volatility. Conclusively, Sun and Yu (2019) considered that the fTGARCH model had some flexibility and superiority to the S&P 500 stock market index.

3.3 Summary of Literature Review

The existing literature has well established the relationship between the stock market and stock market volatility, as well as the relationship between other known shocks and the stock market. However, the literature reveals that not many studies have been carried out regarding measuring volatility during pandemic shocks in the financial services sector. In addition, how big of an impact the pandemic shocks have compared to other known shocks in the stock market. Therefore, this paper will attempt to fill the gap in the literature and make an attempt to analyze the stock price volatility in pandemic shocks in the leading financial services companies in North America. In other terms, this study will present a new and unfamiliar result regarding the impact of pandemic shocks compared to other known shocks to the stock market. To tackle this task, the GARCH model and the TGARCH model will be used due to the previous literature recommending of having both the GARCH model and a GARCH model that considers the asymmetric volatility. These models will be discussed in the methodology section.

4. Methodology

Time series is a sequence of variable's observations at constant time intervals. Four main assumptions have to be fulfilled to consider a sample as time-series data. Firstly, the frequency of the data has to be regular. For instance, the observations in this research, were in daily frequency. Secondly, the observations are correlated in time and are distributed from the earliest to the latest (in this case, the research period was from 2002 to 2020). Thirdly, the data that is described as a process can be realized only once. In other words, it is impossible to proceed with the data again with a different effect. Fourthly, the time-series data should be stationary. Several tests can examine whether this effect is present in the sample (Tsay, 2005). In this research, the time-series data was stationary. Thus, the samples in this research will be considered as the time-series data since they fulfilled the four main assumptions. The precise methodology for the various tests will be presented later in this chapter.

In this paper, four widely known economic shocks in the 21st century was analyzed. Therefore, the data was divided into four sub-periods which was also analyzed separately. In addition, there was not any specific requirements regarding the length of estimation and post-event windows that would present the whole picture of the shock effect. Consequently, the estimation window and the length of the post estimation windows for each sub-period was determined for six months. The minimum number of months contained in the windows were three months. It was considered as difficult to have longer windows because they may had overlapped with each other. Moreover, the longer windows during the energy crisis or H1N1 pandemic coincided with the most unstable period on the market during the financial crisis in 2008. However, the window for the COVID-19 outbreak is still unknown since the pandemic is still an ongoing event in the world. Thus, the window ended on 8th May 2020 for this event. Thus, six months as the estimation windows and the length of the post estimation windows provided a broader view of the events and their impact on the stock market. Ultimately, the time period started from 1st August 2002 and ended on 8th May 2020. The data has been divided as followed (see table 1):

Table 1: Description of the events used in this research

Event Type	Event	Estimation Window
Supply Shock	Energy Crisis	01.08.2002-29.12.2006
Pandemic Outbreak	H1N1	02.09.2008-01.02.2011
Financial Crisis	China Stock Market Crisis	01.11.2013-30.06.2017
Pandemic Outbreak	COVID-19	03.06.2019-08.05.2020

4.1 Models

To analyze how leading financial services companies in North America are affected by pandemic shocks compared to other known shocks in the stock market, three models was performed. These models were the ARCH, the GARCH, and the TGARCH models. The Stata software was used to conduct these models.

The ARCH, the GARCH, and the TGARCH models are the most popular methods used to evaluate the stock return volatility and its asymmetrical effect of positive and negative returns. There is a single order in autoregressive lag (AR) and moving average lag (MA) in all models, which makes the chosen models to: ARCH (1,1), GARCH (1,1), and TGARCH (1,1). The most traditional model, the ARCH (1,1) model, can analyze the volatility. It is similar to the GARCH model, but it requests a higher number of parameters to model the volatility process. The dependent variable in each model is the return in both samples throughout the analyzed sub-period. The TGARCH model upgrades the volatility results by capturing the leverage effects. Thus, the ARCH model and the GARCH model models were considered because there is limited research regarding which model is more superior over the other. Furthermore, the TGARCH model was also considered in this study.

4.2 Diagnostic tests

There are two assumptions that have to be fulfilled before conducting the chosen models. One of them is that the data has to be normally distributed. Another assumption relates to the stationarity of the data. A few diagnostic tests have been conducted to examine these expectations in this study.

4.2.1 Normality tests

First of all, normal distribution signifies that most of the observations are close to the mean. Later on, the histograms are used to check the distribution, skewness, or outliers. If the histogram is skewed to the right or left (for instance, has a longer right tail or left tail), the hypothesis of the normal distribution is rejected. Moreover, the Skewness-Kurtosis test with the additional Jarque-Bera test is conducted to examine whether the skewness and kurtosis correspond to a normal distribution. If the p-value is below 0.05, then the null hypothesis, of skewness and kurtosis equal to 0, should be rejected. The formulas for the: skewness (S) and kurtosis (K) and Jarque-Bera test are as followed (Jarque & Bera, 1987):

$$Skewness = \frac{\widehat{\mu_3}}{\widehat{\delta^3}} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^{3/2}}$$

$$Kurtosis = \frac{\widehat{\mu_4}}{\widehat{\delta^4}} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^{2}}$$

$$Jarque - Bera\ test = \frac{n}{6} \times (S^2 + \frac{1}{4} \times (K-3)^2$$

where the $\hat{\mu}$ is an estimate of central moment and $\hat{\delta}$ is a standard deviation. Moreover, $\bar{x}$ is the sample mean and n is a number of observations.

A second examination that is conducted in this research is the *Lagrange Multiplier* (LM) test. This test verifies for the serial correlation based on the autocorrelation structure. The statistically significant p-value represents that the null hypothesis, which states that there is no presence of the autocorrelation, should be rejected (Bollerslev, Chou & Kroner, 1992). The formula is presented below:

$$Langrange\ Multiplier\ test = Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t} - \ldots - \hat{\beta}_p X_{pt}$$

where β are the estimated coefficients, however, the Y is the time series vector at a time t.

The last conducted test that analyzes the presence of heteroskedasticity is the Breusch-Pagan test. The test examines if the variance of the errors from a regression depends on the outcome of the independent variables. The null hypothesis, which is when the p-value is above 0.05, states that the data is homoscedastic. Therefore, the same variance occurs in each variable (Breusch & Pagan, 1979). The formula is as followed:

$$Breusch - Pagan\ test = n \times R^2$$

where the n is described as a number of observations, whilst the R square (R^2) is the regression of squared residuals from the original regression.

4.2.2 Stationarity

Another assumption that has to be fulfilled before conducting the models, relates to the stationarity of the data. The characteristic of the process of stationarity is that the mean, variance, and autocorrelation structure do not change over time (Nezhad, 2012). Typically, stock market returns are stationary since the returns are the first difference in the prices. Firstly, the stationarity of the data can be conducted by creating a graph that shows the plot of the time series. Secondly, some tests help identify the behavior of the time series. Stationarity tests are the most typical tests regarding the return series. The stationarity in this research is analyzed using the Augmented Dickey-Fuller (ADF) test. This test is better for larger time series models since it adds lagged differences to the simpler Dickey-Fuller test. It presents whether the data series has a unit root or not. Unit root signifies that the data are not stationary, and its existence is shown by the null hypothesis (γ=0). However, the statistically significant p-value presents that the data is stationary and that the ARCH model can be estimated (γ<0). The formula for the ADF test is as followed (Stock and Watson, 2007):

$$\Delta Y_t = \alpha_0 + \beta_t + \delta Y_{t-1} + \gamma_1 \Delta Y_{t-1} + \gamma_2 \Delta Y_{t-2} + \cdots + \gamma_p \Delta Y_{t-p} + \varepsilon_t$$

where ΔY presents change in a variable over time. α in this formula is considered as a constant, whilst β is the coefficient of a time trend. γ is the coefficient for the lagged level of the series and p is a number of lags of the autoregressive process.

4.3 Research Validity

The reliability of the chosen research approach, a quantitative approach, is considered as high. Denscombe (2009) states that a sample greater than 300 observations are viewed to provide a reliable estimation of the research's results. This thesis has gathered two samples from 29 companies in the financial services sector and 30 companies from diverse sectors. A total of 4637 observations have been conducted in each sample. As mentioned earlier, we have an 18-

years period, which is considered as long enough as a period for being able to capture the changes in stock market volatility overtime during different event periods. In essence, this reduces the risk of a biased outcome (Denscombe, 2009).

Furthermore, due to the recommendations from previous studies in the literature review section, three different models have been included to estimate the stock market volatility. These are namely: the ARCH, the GARCH model, and the TGARCH model. Three models have been included due to more robust and reliable outcomes.

However, a weakness with the study is the exclusion of a large number of companies from the original sample, where, for instance, not all sub-sectors were included due to not fulfilling the requirements of having the top ten companies. Therefore, the sample is less diversified and could lead to a biased perspective towards the whole financial services sector in North America. However, to increase the research validity of this study, we have also decided to compare the first sample of the financial services sector to other sectors that are listed in Dow Jones Industrial Average Index and examine how these sectors react to pandemic shocks and other known shocks.

5. Data description

Two samples were used in this research. First of all, the first sample consisted of the performance of leading financial services companies in North America that were active from 1st August 2002 to 8th May 2020, which makes the research period of this paper. The choice of financial services sector was made by the fact of its increasingly influential role in society. The eighteen-years period covered several important shocks to the stock market. Therefore, this period was considered as a relevant and sufficient time period to observe how the price volatility has changed in the financial services sector in North America.

The data was collected by using the DataStream platform. The initial sample was composed of the historical prices of the top ten companies of 52 sub-sectors of the financial services companies that are classified by the *North American Industry Classification System* (NAICS). The requirements that were set up for a company to be included in our sample were as following:

1. A Finance and/or Insurance company included in the NAICS.
2. Each sub-sector has top ten companies.
3. Active during the research period: 01.08.2002 to 08.05.2020.

All companies fulfilled the first requirement due to the list were retrieved from the financial services sector. Nevertheless, three sub-sectors were excluded from the initial sample due to not having ten top companies in the respective ranking. Subsequently, certain companies were classified in other sub-sectors as well, where those sub-sectors had to be eliminated due to it not meeting the requirements of having the top ten companies. Simply put, these companies did not fulfill the second requirement. After excluding the same companies and the sub-sectors, the sample contained 370 companies. However, most of companies were not active from 2002. Consequently, the third requirement was not fulfilled and companies with insufficient data were removed. Furthermore, due to an error in the DataStream platform, four companies were excluded from the sample. The prices for those companies were fixed for the whole research period. This ultimately led to the sample consisting of 29 companies. The index was conducted using an equal weighted-average arithmetic mean.

Second of all, the second sample included the performance of companies recorded in the Dow Jones Industrial Average index. This index consists of thirty blue chip companies. These companies are listed on two U.S. stock exchanges: NYSE and NASDAQ. The Dow Jones Industrial Average index was selected because it is one of the most popular stock market indices in the world. Moreover, it uses its price-weighted index method. The data was collected using the same platform as in the first sample.

Furthermore, the data included stock prices with a daily frequency during the research period. Therefore, both samples had 4637 observations during the whole research period. The data was converted into logarithmic values. The formula is presented below:

$$Logarithm\ of\ the\ returns_t = \ln\left[\frac{Price_t}{Price_{t-1}}\right] \approx \frac{Price_t - Price_{t-1}}{Price_{t-1}}$$

Figures 1 and 2 present the prices of the average performance of the two samples during the research period. The highest sudden drop in the analyzed subperiod is seen during the COVID-19 outbreak in 2019-2020.

Figure 1: Daily prices of the average performance of 29 companies from 2002 to 2020

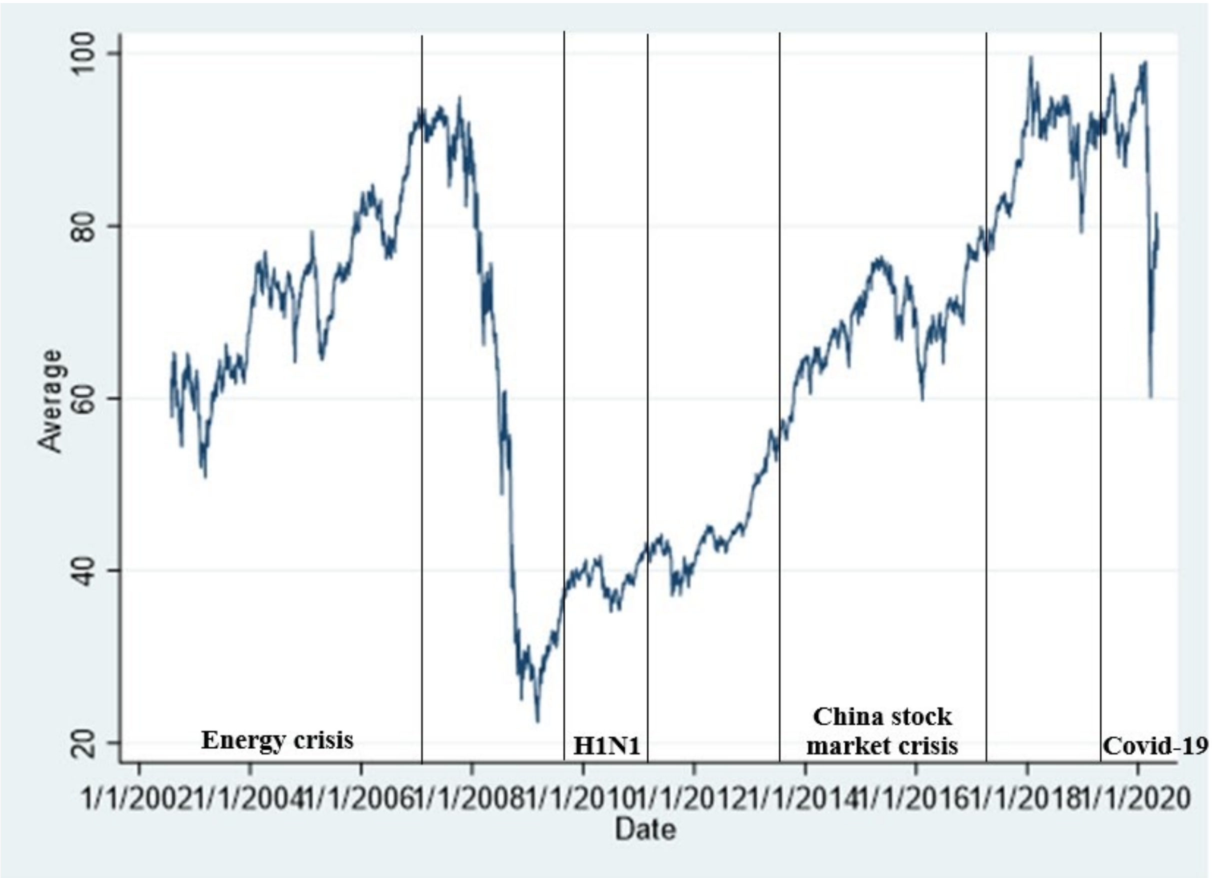
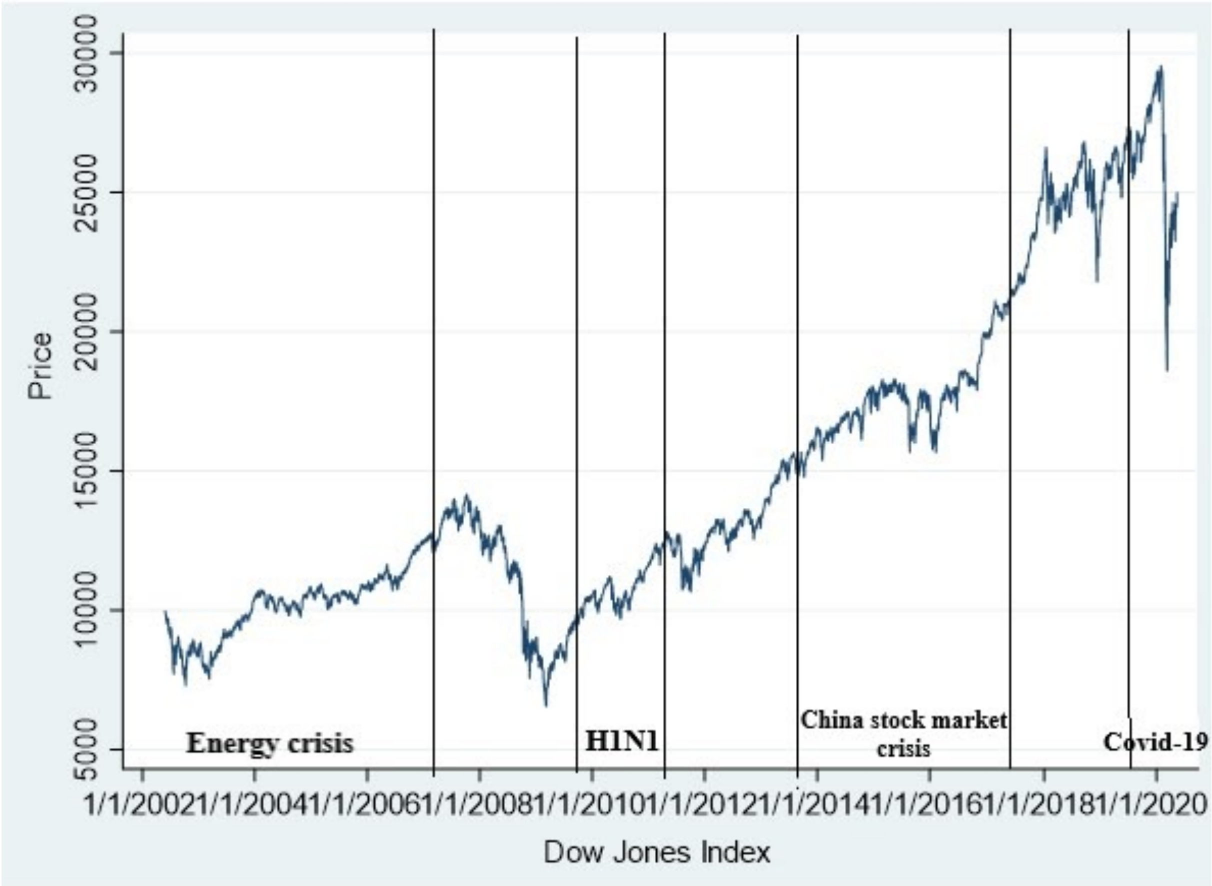


Figure 2: Daily prices of the average performance of Dow Jones 30 companies from 2002 to 2020



6. Main Findings

After presenting the data description of this study, this chapter will present the main findings concerning the shocks specific variables and volatility estimations. Later on, the outcomes of the asymmetrical effects of returns will be described.

6.1 Diagnostic tests

The results of the diagnostic tests examining the normal distribution and the stationarity are presented in the subsections below.

6.1.1 Normality tests

The histograms were conducted to check the normality of the two samples. Based on histograms and additional lines, it can be assumed that the observations were normally distributed. Moreover, the variables were showing the leptokurtic effect, which means that they are spread close to the mean. Another characteristic feature of these histograms was the relatively high peak in the center. It may indicate a high level of kurtosis, which implies the occurrence of more extreme returns than usual. The phenomena of extreme returns often occur during economic shocks. The results of the skewness were considered as small in each sub-sector, except during the COVID-19 outbreak. Thus, the distribution of the data was symmetric, except the moderately negative skewness observed during the COVID-19 outbreak (see figures 3-10).

Figure 3: The histogram of the average performance of 29 companies during the energy crisis

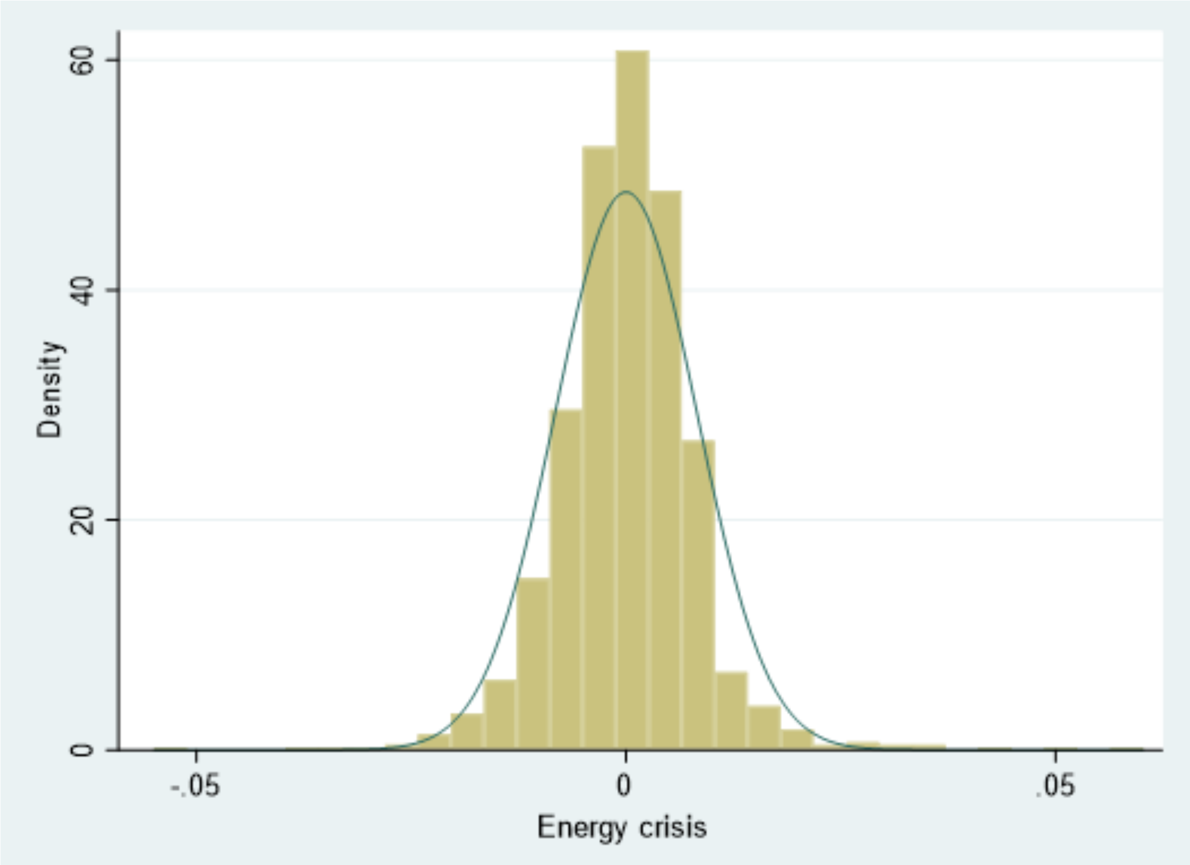


Figure 4: The histogram of the average performance of the Dow Jones 30 companies during the energy crisis

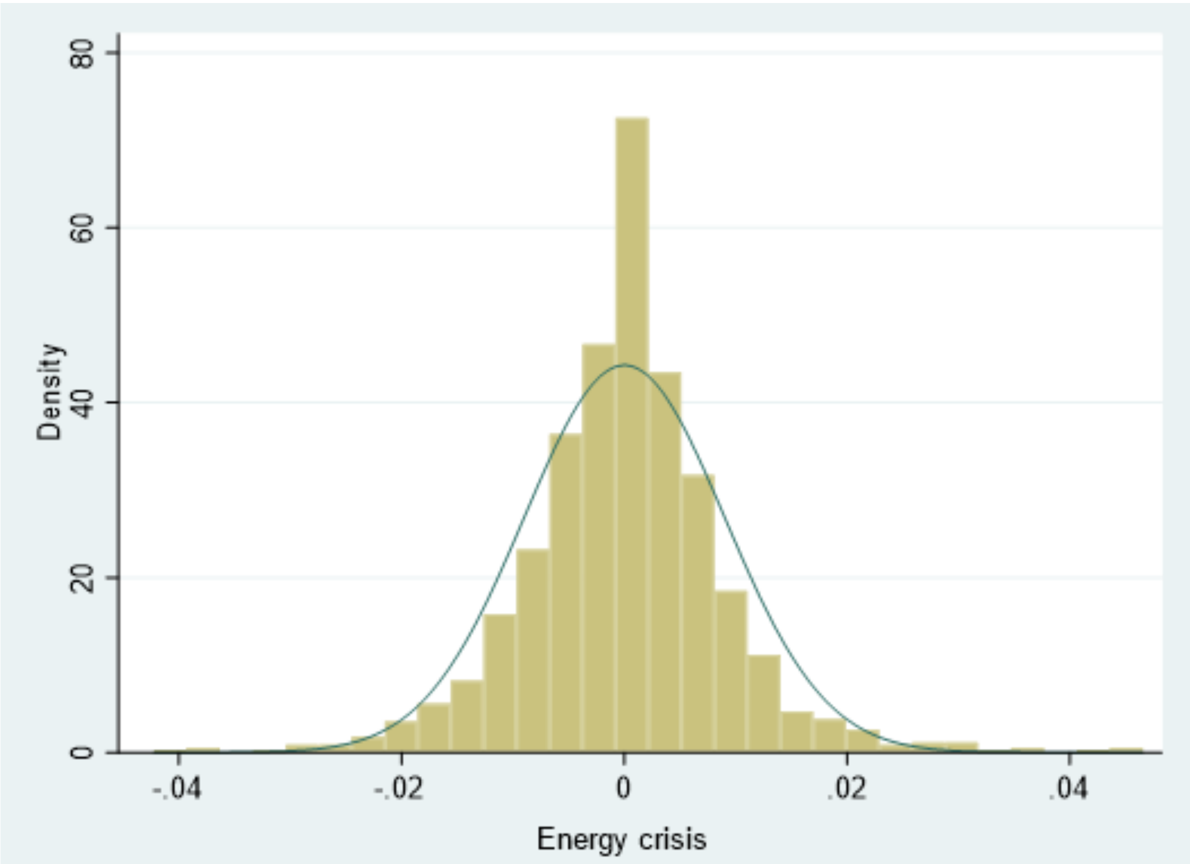


Figure 5: The histogram of the average performance of 29 companies during the H1N1 outbreak

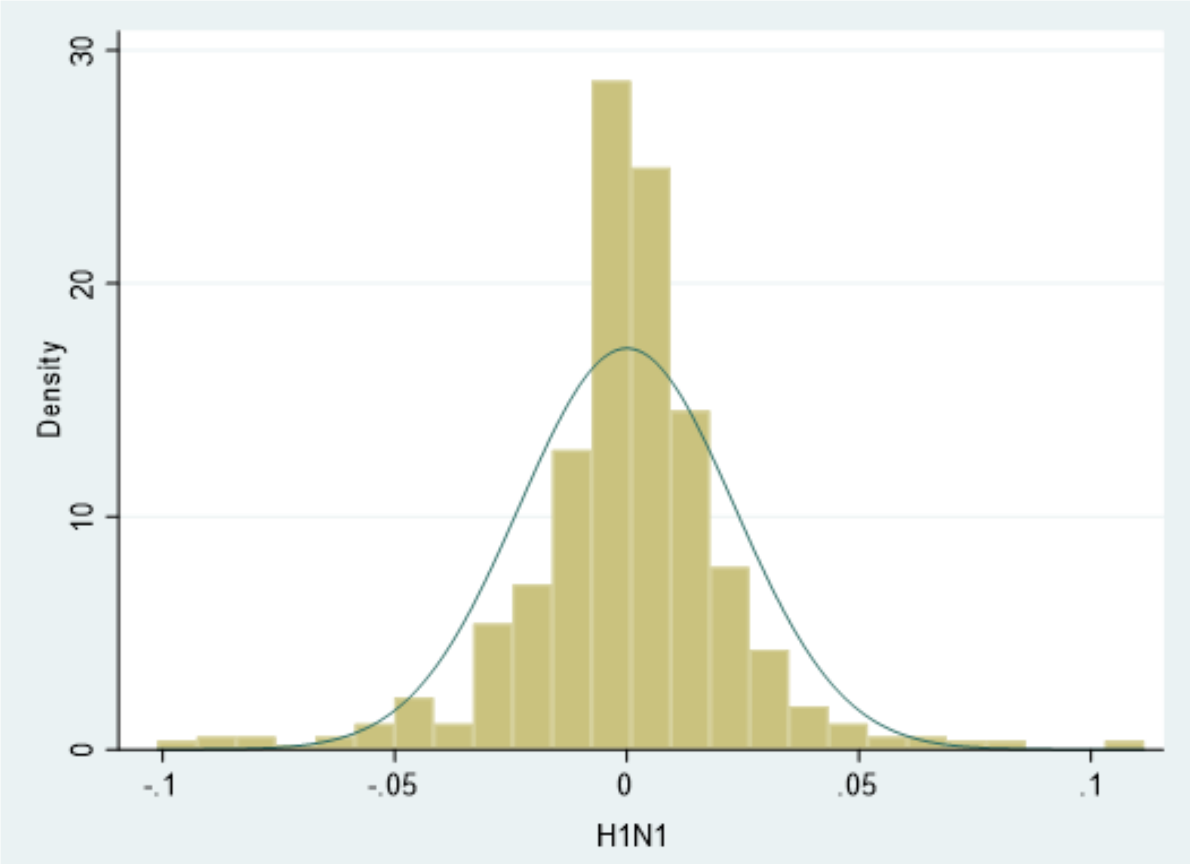


Figure 6: The histogram of the average performance of the Dow Jones 30 companies during the H1N1 outbreak

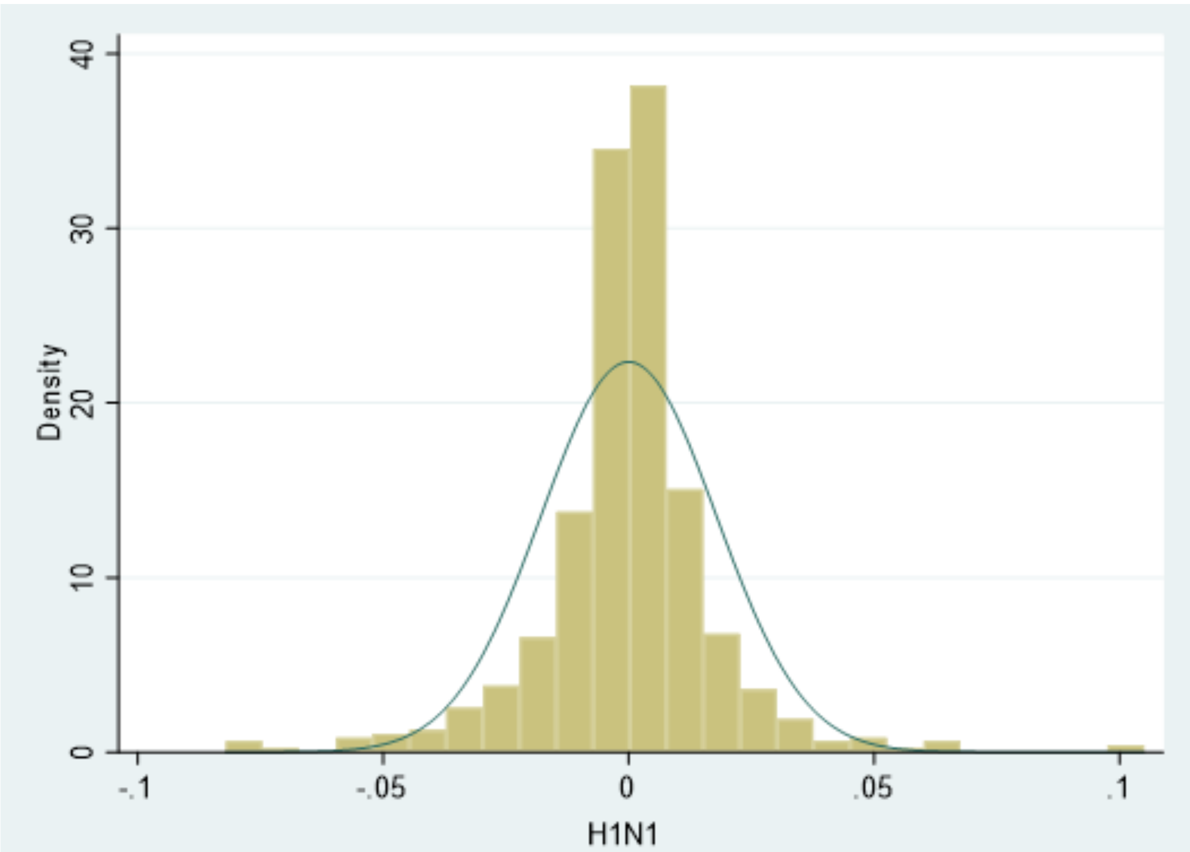


Figure 7: The histogram of the average performance of 29 companies during the China Stock Market crisis

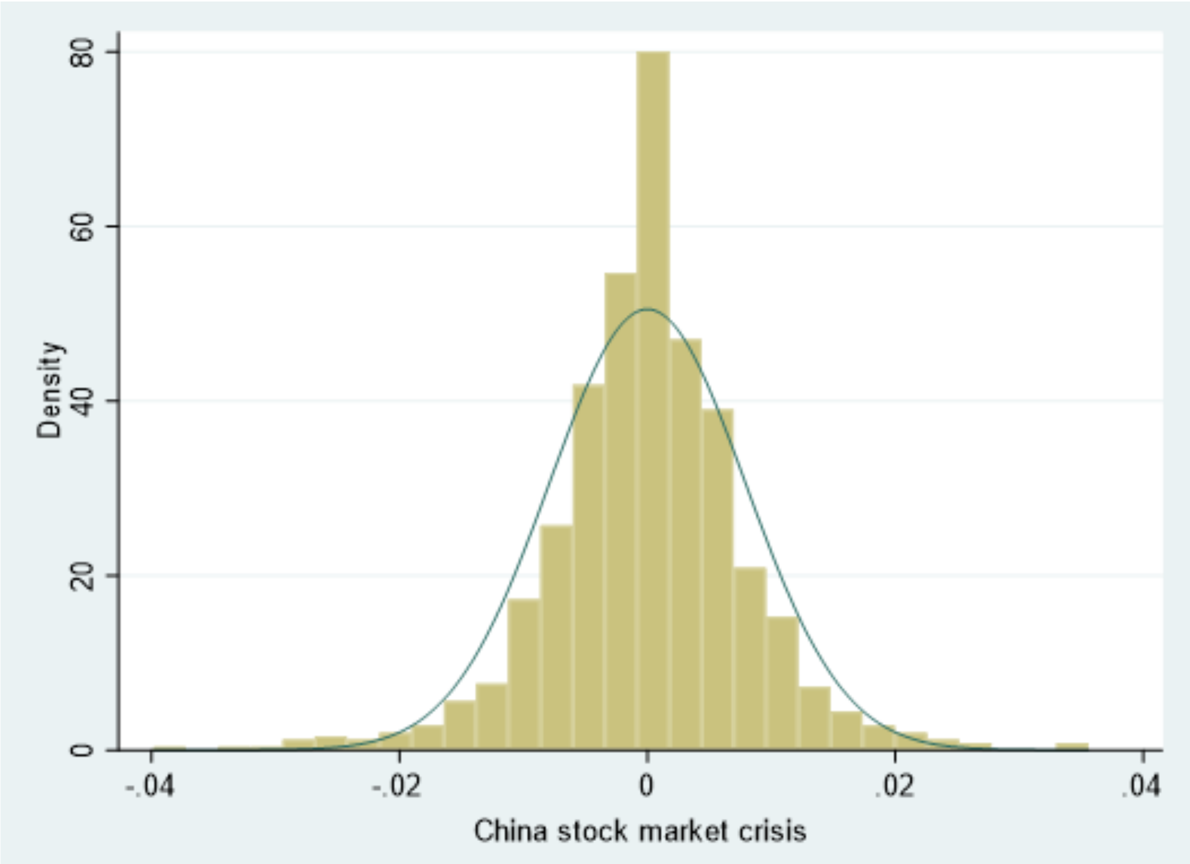


Figure 8: The histogram of the average performance of the Dow Jones 30 companies during the China Stock Market crisis

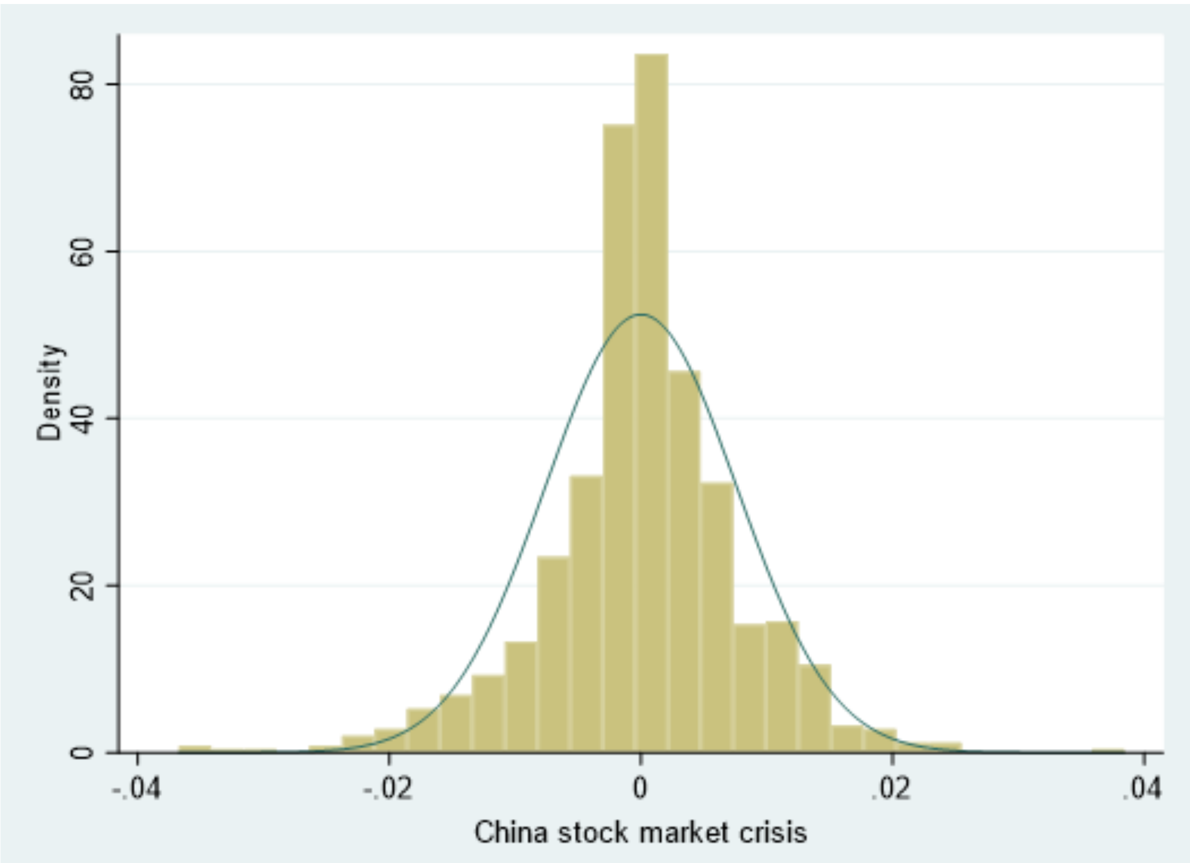


Figure 9: The histogram of the average performance of 29 companies during the COVID-19 outbreak

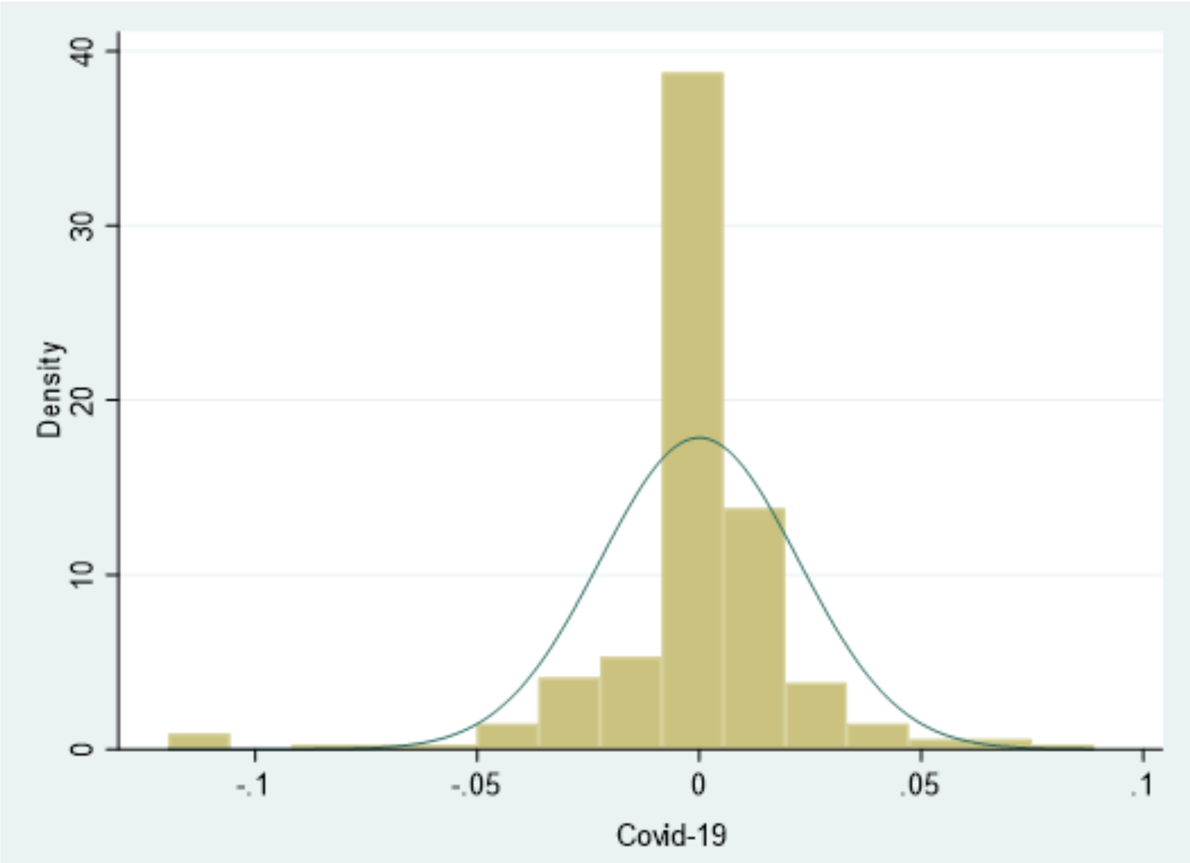
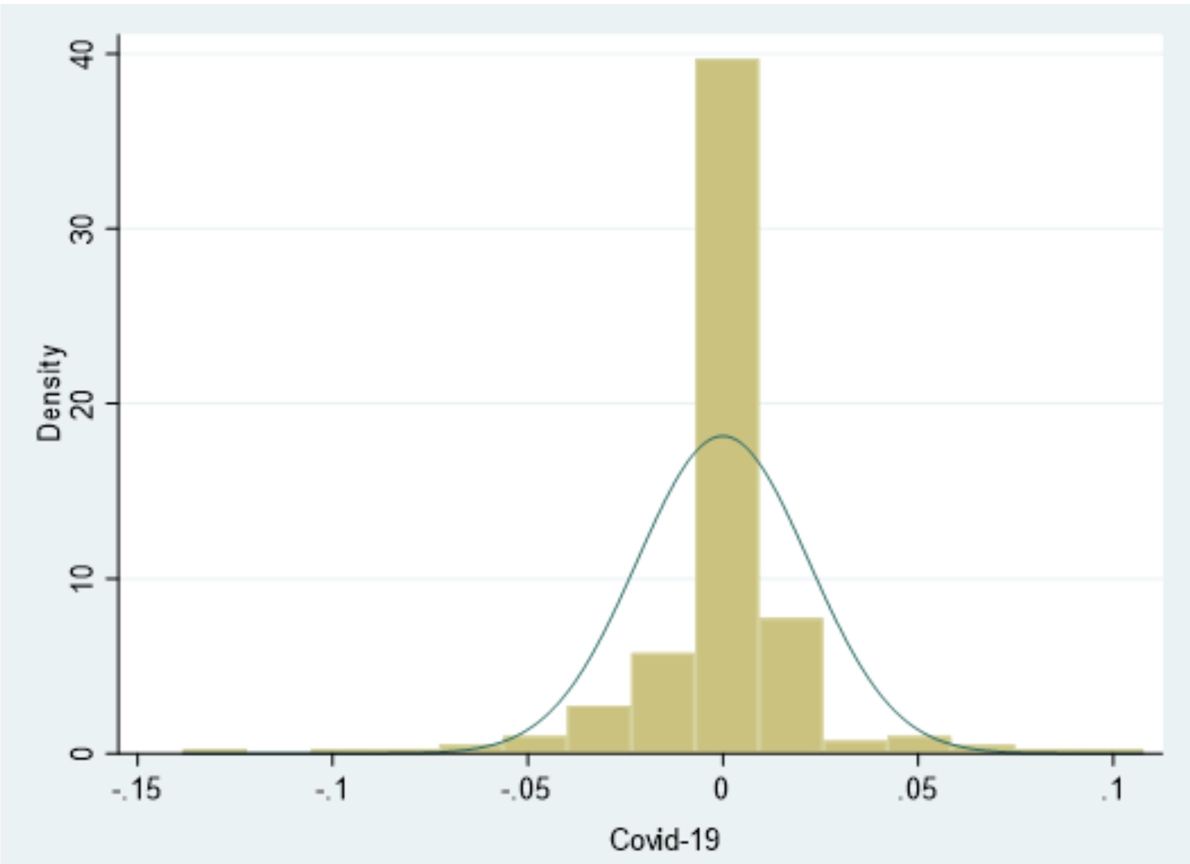


Figure 10: The histogram of the average performance of the Dow Jones 30 companies during the COVID-19 outbreak



The p-values in both samples were below 0.05. Therefore, the null hypothesis, where the skewness and kurtosis were equal to 0, was rejected. Nevertheless, the results of the Skewness-Kurtosis test and Jarque-Bera test were overly sensitive since the sample consists of a small number of observations. The longest sub-period, the energy crisis, had 1152 observations. Therefore, due to the small amount of observations, the results of these tests were excluded from this research.

The results of the Lagrange Multiplier test for both samples were below 0.05. Therefore, the null hypothesis was rejected and there was evidence of the presence of the autocorrelation. It also implies that the returns in each sub-period were heteroskedastic. Thus, the variability of the data was not equal during each sub-period, where the returns were constantly changing. Moreover, the variance was not constant. The heteroskedasticity can also be verified by using the Breusch-Pagan test. All the results of the p-value were lower than 0.05. Accordingly, heteroskedasticity in all sub-periods was presented. The results, performed in this section, demonstrate that most of the assumptions were fulfilled to perform the chosen models for this study.

6.1.2 Stationarity

The stationarity can be observed in figures 11 and 12. The Augmented Dickey-Fuller test was below 0.05 in every sub-period for both samples. Therefore, the null hypothesis was rejected, and the stationarity effect appeared in the data. The highest volatility of the examined returns in the first sample can be observed during the COVID-19 pandemic (see figure 11). In meanwhile, figure 12 describes the returns of the companies from the Dow Jones index present significantly high volatility only during the COVID-19 pandemic (see figure 12).

Figure 11: Daily returns of the average performance of 29 companies from 2002 to 2020

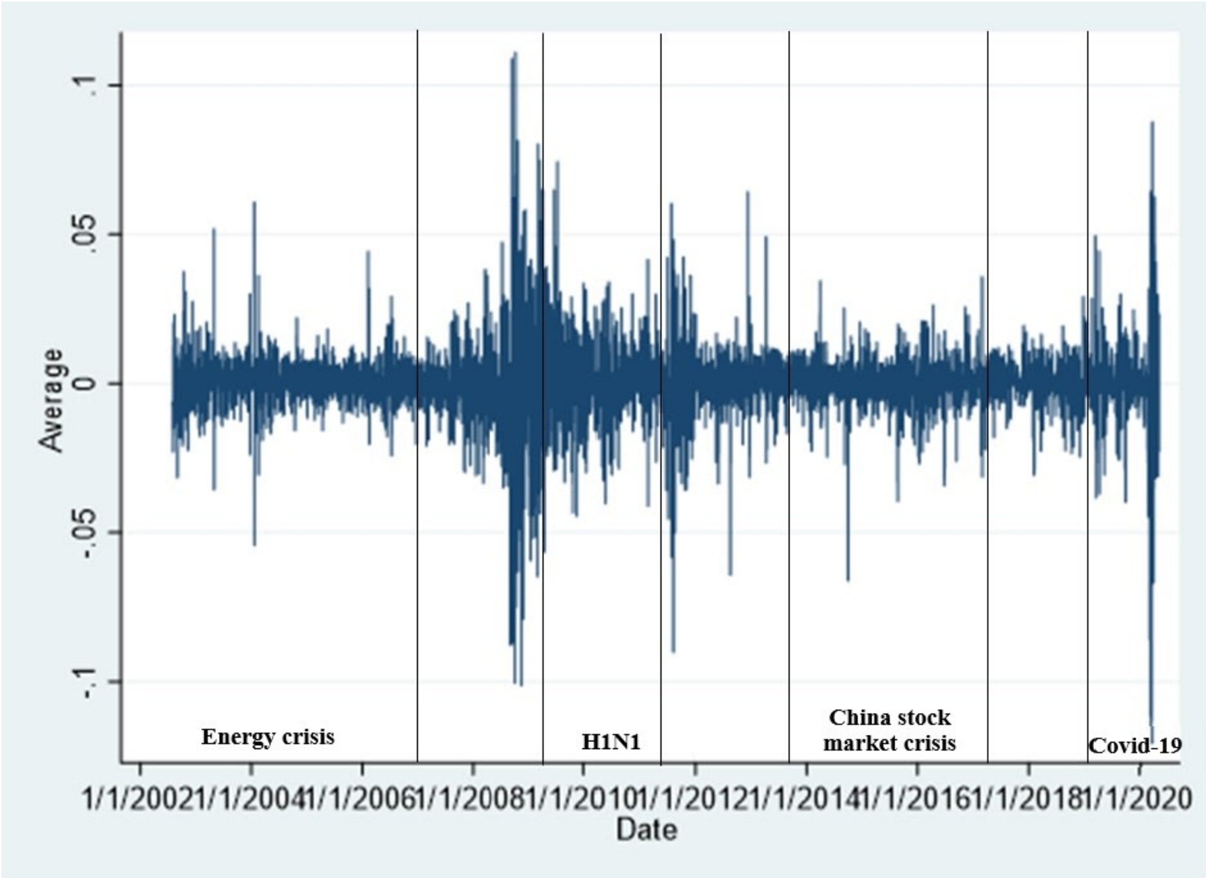
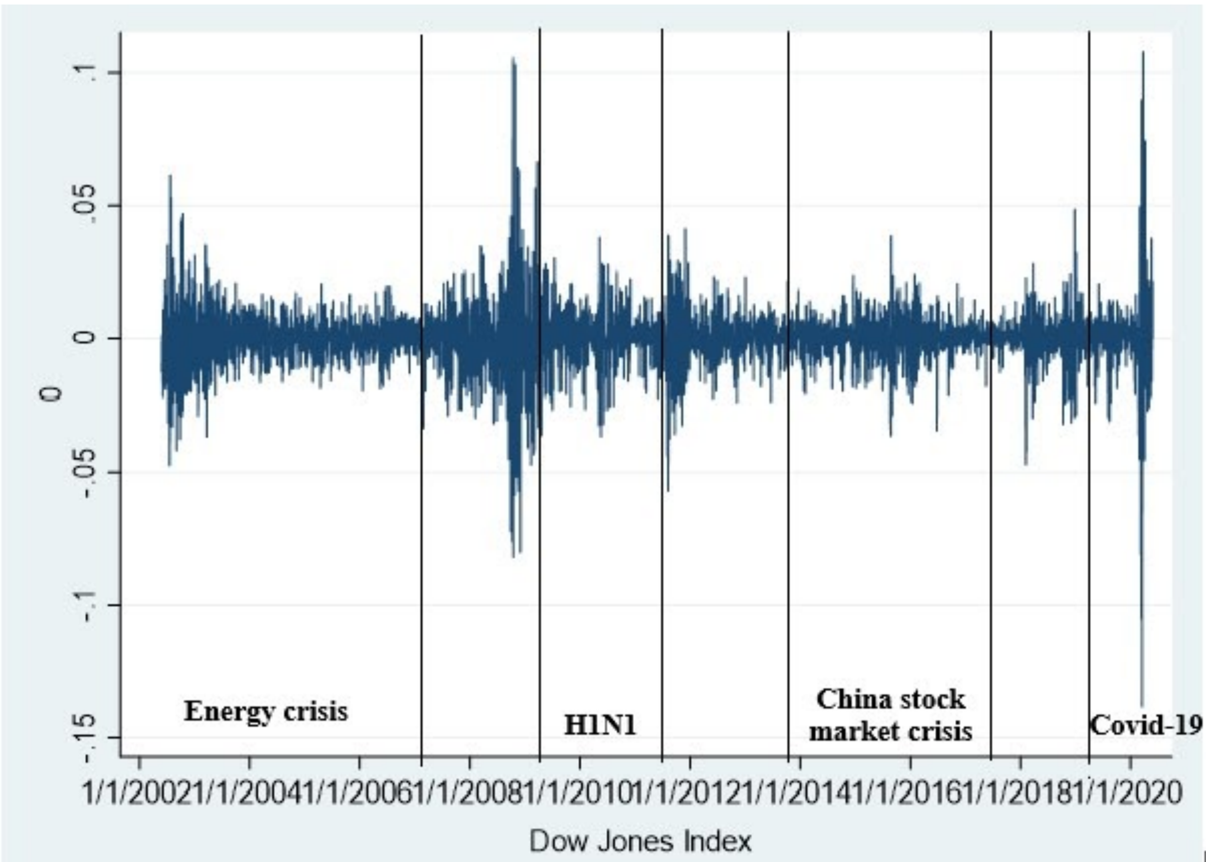


Figure 12: Daily returns of the average performance of the Dow Jones 30 companies from 2002 to 2020



The variables from Table 2, such as variance, standard deviation, skewness, and kurtosis, give more detailed information about the distribution in the first sample. Table 2 presents a descriptive statistic for four analyzed sub-periods. The mean of pandemic shocks was negative, however, the means of the other two shocks were positive. These results showed that the financial services sector has achieved more losses than profits during the pandemic outbreak. Nevertheless, the pandemic sub-periods were shorter and have a smaller number of observations. The highest mean was equal to 0.00062 and was observed during the energy crisis. All the results of the variance and standard deviation were low, which means that the values were close to the mean. Nonetheless, pandemic shocks presented higher variance than the other known shocks. In the long run, the deviation of the pandemic shocks' observations from its mean was more spread out (see table 2).

Table 2: Summary statistic of the average performance of 29 companies from 2002 to 2020

Event	Period	Mean	Standard Deviation	Minimum	Maximum	Variance
Energy Crisis	**01.08.2002-29.12.2006**	0.00062	0.00822	-0.05433	0.06083	0.00007
H1N1	**02.09.2008-01.02.2011**	-0.00033	0.02317	-0.10146	0.11112	0.00054
China Stock Market Crisis	**01.11.2013-30.06.2017**	0.00025	0.00790	-0.04690	0.02774	0.00006
COVID-19	**03.06.2019-08.05.2020**	-0.00111	0. 02235	-.012071	0.08771	

Table 3 presents the summary statistics for the second sample. The means during pandemic outbreaks were lower than during the other known shocks. The same conclusion could be drawn from the results of the first sample. Moreover, the means for other known shocks showed a similar result. Nevertheless, the standard deviation and the variance were higher during pandemic outbreaks. The lowest minimum and the highest maximum variable from all sub-periods were observed during the COVID-19 outbreak (see table 3).

Table 3: Summary statistic of the average performance of the Dow Jones 30 companies from 2002 to 2020

Event	Period	Mean	Standard Deviation	Minimum	Maximum	Variance
Energy Crisis	**01.08.2002-29.12.2006**	0.00035	0.00901	-0.04189	0.04690	0.00008
H1N1	**02.09.2008-01.02.2011**	0.00007	0.01784	-0.08201	0.10508	0.00032
China Stock Market Crisis	**01.11.2013-30.06.2017**	0.00033	0.00761	-0.03640	0.03875	0.00006
COVID-19	**03.06.2019-08.05.2020**	-0.00008	0.02198	-0.13842	0.10764	0.00048

6.2. Results from the Models' Estimations

Table 4 presents the results of the ARCH (1,1) model for the 29 companies from the first sample. The coefficients and z-Statistic for the pandemic outbreaks were higher than during other known shocks. Moreover, the highest coefficient of the variance parameter occurred during the COVID-19, which showed a result of above 1. The standard errors for the energy crisis and the China Stock Market Crisis showed almost similar results. The p-value was highly significant in each sub-period (see table 4).

Table 4: Volatility estimation for the ARCH model from Stata for 29 companies during research sub periods

Economic shocks	Period	Coefficient	Standard Error	z-Statistic	P-value
Energy crisis	**01.08.2002-29.12.2006**	0.11966	0.03264	3.67	0.000
H1N1	**02.09.2008-01.02.2011**	0.41029	0.05011	8.19	0.000
China Stock Market crisis	**01.11.2013-30.06.2017**	0.16799	0.03098	5.42	0.000
COVID-19	**03.06.2019-08.05.2020**	1.15005	0.09573	12.01	0.000

The ARCH (1,1) results for Dow Jones companies are shown in table 5. By comparing these two samples, it can be observed that there were a lot of similarities between them. For instance, the coefficient during the COVID-19 outbreak had the highest value and was above 1. In addition, the standards errors were also below 0.1. The highest z-statistic were observed during the pandemic shocks. Moreover, p-values equal to 0 were observed in each sub-period for both cases (see table 5).

Table 5: Volatility estimation for the ARCH model from Stata for the Dow Jones 30 companies during research sub periods

Economic shocks	Period	Coefficient	Standard Error	z-Statistic	P-value
Energy crisis	01.08.2002-29.12.2006	0.20563	0.03104	6.62	0.000
H1N1	02.09.2008-01.02.2011	0.58959	0.05305	11.11	0.000
China Stock Market crisis	01.11.2013-30.06.2017	0.34001	0.04294	7.92	0.000
COVID-19	03.06.2019-08.05.2020	1.28823	0.08842	14.57	0.000

The results of the GARCH (1,1) model for the 29 companies in the financial services sector are presented in Table 6. The coefficients on the lagged variance in the GARCH (1,1) method were above 1 during the energy crisis, whereas the lowest coefficient was during the COVID-19 outbreak. In the meanwhile, the standard errors were considered as low. The highest outcome of the standard error, which can be found during the China Stock Market crisis, was equal to 0.236. The highest and the lowest values of z-statistics were during other known shocks. The lowest z-statistic was equal to 3.95 which was during the China Stock Market crisis, whereas the highest outcome, which was during the energy crisis, was 9.80. The p-value of the variance of the returns was significant in each sub-period (see table 6).

Table 6: Volatility estimation for the GARCH model from Stata for 29 companies during research sub periods

Economic shocks	Period	Coefficient	Standard Error	z-Statistic	P-value
Energy crisis	01.08.2002-29.12.2006	1.46400	0.14940	9.80	0.000
H1N1	02.09.2008-01.02.2011	0.73805	0.08146	9.06	0.000
China Stock Market crisis	01.11.2013-30.06.2017	0.93167	0.23577	3.95	0.000
COVID-19	03.06.2019-08.05.2020	0.25933	0.05817	4.46	0.000

The value of GARCH coefficients in the second sample was gradually decreasing. The highest value was observed during the energy crisis with a result of 1.15149, however, the lowest one was through the COVID-19 pandemic with a result of 0.14768. The standard errors during other known shocks were higher compared to the pandemic shocks. The results of the z-statistic for the energy crisis and the H1N1 pandemic were almost the same. Moreover, all the p-values were highly significant (see table 7).

Table 7: Volatility estimation for the GARCH model from Stata for the Dow Jones 30 companies during research sub periods

Economic shocks	Period	Coefficient	Standard Error	z-Statistic	P-value
Energy crisis	01.08.2002-29.12.2006	1.15149	0.12524	9.19	0.000
H1N1	02.09.2008-01.02.2011	0.75581	0 .07869	9.60	0.000
China Stock Market crisis	01.11.2013-30.06.2017	0.57593	0.09713	5.93	0.000
COVID-19	03.06.2019-08.05.2020	0.14768	0.03645	4.05	0.000

Results of coefficients occurring in the TGARCH (1,1) model in the first sample are presented in Table 8. The coefficients during the pandemic shocks were negative. Meanwhile, the outcomes of the standard error were different in each sub-period. The lowest value of z-Statistic was
-3.06 which could be found during the COVID-10 outbreak, whilst the highest value was 3.23 during the China Stock Market crisis. As in the case of the negative coefficients, during the pandemic shocks, the z-statistic were shown as negative as well. However, the p-values in the TGARCH (1,1) model presented a higher result than in the ARCH (1,1) and the GARCH (1,1) models. The p-value during the energy crisis and H1N1 outbreak were not significant. Thus, the hypothesis of the absence of asymmetry was rejected in this sub-period (table 8).

Table 8: Asymmetric volatility estimation for the TGARCH model from Stata for 29 companies during research sub periods

Economic shocks	Period	Coefficient	Standard Error	z-Statistic	P-value
Energy crisis	01.08.2002-29.12.2006	0.02938	0.01911	1.54	0.124
H1N1	02.09.2008-01.02.2011	-0.14332	0.06562	-2.18	0.290
China Stock Market crisis	01.11.2013-30.06.2017	0.10295	0.03184	3.23	0.001
COVID-19	03.06.2019-08.05.2020	-0.87373	0.28551	-3.06	0.020

Whilst performing the TGARCH (1,1) model for the second sample, all the coefficients were negative. The standard errors in both samples were below 0.01, except for the COVID-19 outbreak in the TGARCH (1,1) model, where the value was above 0.27. Each z-Statistic outcome in this model was negative. In addition, the p-values for the pandemic shocks were shown as insignificant. During the H1N1 outbreak, the p-value was equal to 0.058, however, the p-value of COVID-19 was almost 4 times higher (see tables 9).

Table 9: Asymmetric volatility estimation for the TGARCH model from Stata for the Dow Jones 30 companies during research sub periods

Economic shocks	Period	Coefficient	Standard Error	z-Statistic	P-value
Energy crisis	01.08.2002-29.12.2006	-0.16112	0.03637	-4.43	0.000
H1N1	02.09.2008-01.02.2011	-0.12731	0.06721	-1.89	0.058
China Stock market crisis	01.11.2013-30.06.2017	-0.27963	0.08665	-3.23	0.001
COVID-19	03.06.2019-08.05.2020	-0.32802	0.27108	-1.21	0.226

7. Analysis & Discussion

This section will provide the analysis and discussions of the main findings presented above. Moreover, ensure answers to the research question stated in the introduction will be presented, and if the hypothesis of this paper could be proven from the result.

7.1 Analysis & Discussion of the Results

The hypothesis of this paper is: pandemic shocks have lower volatility than other known shocks. In line with the information stated in Tables 2 and 3, the data during the pandemic shocks was more spread out. Simply put, the prices were more volatile, and the stocks were riskier. With this knowledge, it is safe to realize that the results presented so far indicate higher volatility of the pandemic shocks than what the hypothesis of this paper considered. However, the hypothesis can be challenged since the pandemic shocks had a lower number of observations than other known shocks. Realized volatility is the sum of squared returns divided by the number of observations. Thus, dividing by a smaller number of observations gives higher results. Moreover, the sample of the COVID-19 outbreak does not consist of a post estimation window. This window occurs after the shock, which ultimately suggests that the volatility should not be as high as during the event. In practice, the sample without a post estimation window will present higher volatility in total.

The ARCH(1,1) model is the basic method for analyzing the volatility of returns. The coefficients of variance in this model were small except during the COVID-19 pandemic. Thus, there was no unconditional variance in this sub-period. The ARCH (1,1) model was also used by the Sakata and White (1998) in their research. However, Awartani and Corradi (2005) could prove that the GARCH model is a better choice compared to the ARCH model. Nevertheless, modern studies prefer other models for time series such as the developed version, the GARCH model, and the models that consider the asymmetric volatility. As for how Kang et al. (2009) and Wei et al. (2010) suggested that nonlinear GARCH-class models (in this case, the TGARCH model) outshined the linear GARCH-class model (in this case, the GARCH model), this paper chose to focus on the results of both the GARCH(1,1) and the TGARCH(1,1) models.

The coefficient of the GARCH(1,1) model may show that the data during the energy crisis did not fit the model. The reason being is that the stationarity condition that the sum of ARCH and GARCH effect in this model was less than 1 and higher than 0, which was not fulfilled in this period. Therefore, it implied that the unconditional variance for GARCH (1,1) did not exist. On the other hand, the lowest coefficient of the GARCH(1,1) effect in both samples was estimated during the COVID-19 outbreak. The reason for it may be that this sub-period did not have the post estimation window. As mentioned earlier, COVID-19 pandemic outbreak is currently still an ongoing event. Therefore, it is yet possible to examine how long the large volatility changes will persist.

The difference in the two samples was related to the coefficients during the H1N1 pandemic and the China Stock Market crisis. In the first sample, the coefficient of the China Stock Market crisis in the return presented a higher value than the coefficient of the pandemic outbreaks. The high outcome during these shocks shows that large changes in the volatility remained for a longer time in the future. This result may confirm the hypothesis that the financial services sector reacts more to other known shocks than to pandemic shocks. This result corresponded to Charles and Darne (2014) result, where large volatility shocks are principally due to events such as the financial crisis, which in this case is the China Stock Market crisis. On the other hand, the coefficient of the H1N1 pandemic in the second sample was higher than during the China Stock Market crisis. Therefore, the pandemic outbreak had a greater impact on other sectors' performance. As stated by the U.S.-China Economic and Security Review Commission (2016;2017), the U.S. financial markets were heavily influenced by the China Stock Market crisis. The results from our first sample showed that the financial services sector in North America was also affected by the China Stock Market crisis. However, the second sample where the other sectors represented, showed that the H1N1 outbreak had a greater impact than the China Stock Market crisis. Hence, it is unclear to determine whether they were truly heavily affected by the crisis. Thus, the results of the second sample may not present an unambiguous answer regarding the hypothesis.

As mentioned earlier, Kang et al. (2009) and Wei et al. (2010) suggested nonlinear GARCH-class models (the TGARCH model) over linear GARCH-class models (the GARCH model). Thus, the authors believed that the TGARCH model is a more reliable model compared to the GARCH model. Therefore, the results from the TGARCH model in this thesis have a higher impact on the decisions whether the research hypothesis could be proven or not. The results of the coefficients from the first sample in the TGARCH (1,1) model were not significant in the first two sub-periods (see Table 8). Nevertheless, a higher p-value did not imply that the model is inaccurate. The threshold slope term was negative during pandemic shocks. In other words, this shows that during these sub-periods, the high positive shocks (good news that decreases the stock prices) increased the volatility more than the negative shocks (bad news that increases the prices of the stock). It presented the behavioral asymmetry of the shock. Furthermore, the results were not in line with the leverage effect, which stated that there was a negative relationship between volatility and stock price. Nonetheless, the logarithmic specification of this model will not let the variance to be negative. Thus, the coefficient in the TGARCH (1,1) model had the possibility of showing a result in a negative form. The high value of the coefficient describes negative economic market conditions. However, in the case of the energy crisis and China Stock Market crisis, the results were recognized as not as large. The result of the China Stock Market crisis was expected since the stock crash was more specific to Chinese companies and the companies analyzed in this paper were from North America. In other terms, the coefficients during analyzed crises were positive. In addition, negative shocks during the crises increased the volatility more than positive shocks. During each sub-period, there were more negative shocks (increases in prices) than positive shocks (drops in prices) (see figures 13 and 14). Therefore, there is another argument confirming the hypothesis of this research since the pandemic shocks have higher volatility during positive shocks.

Figure 13: Number of positive shocks of the average performance of 29 companies during four sub periods

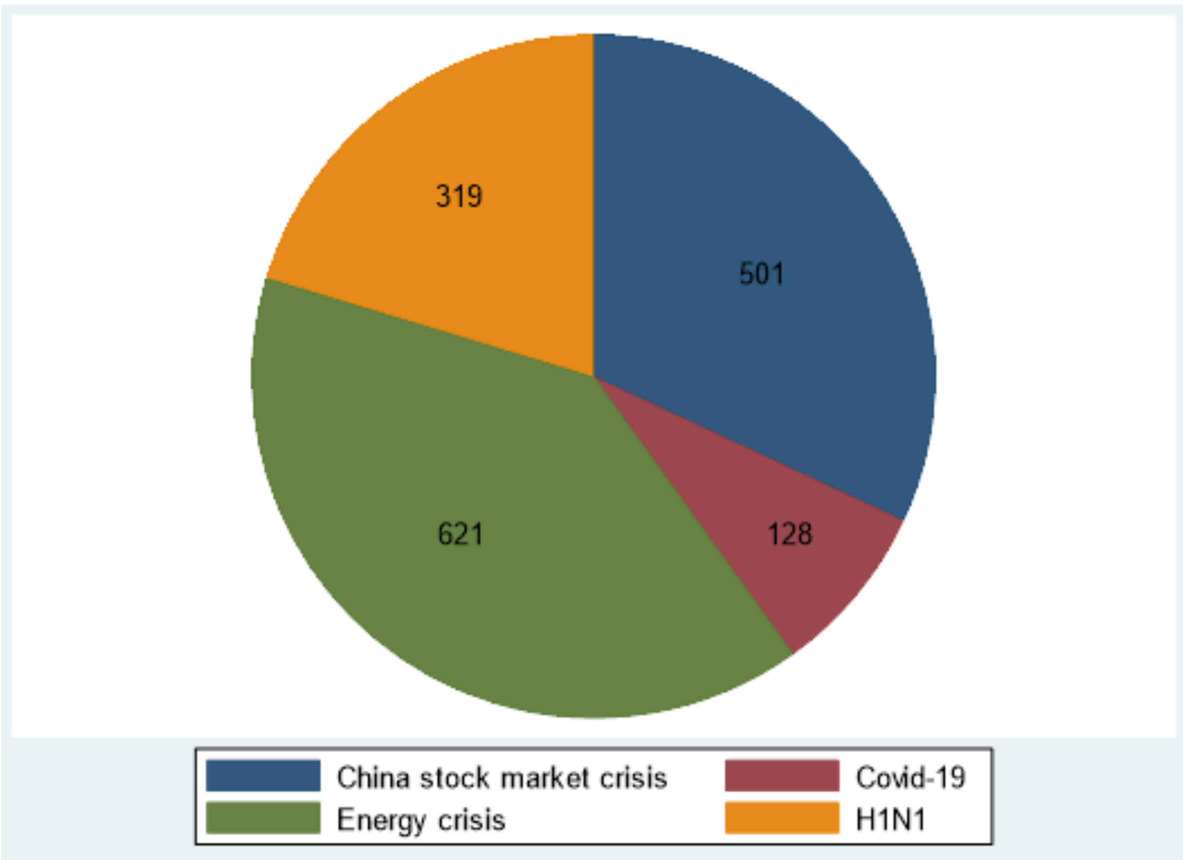
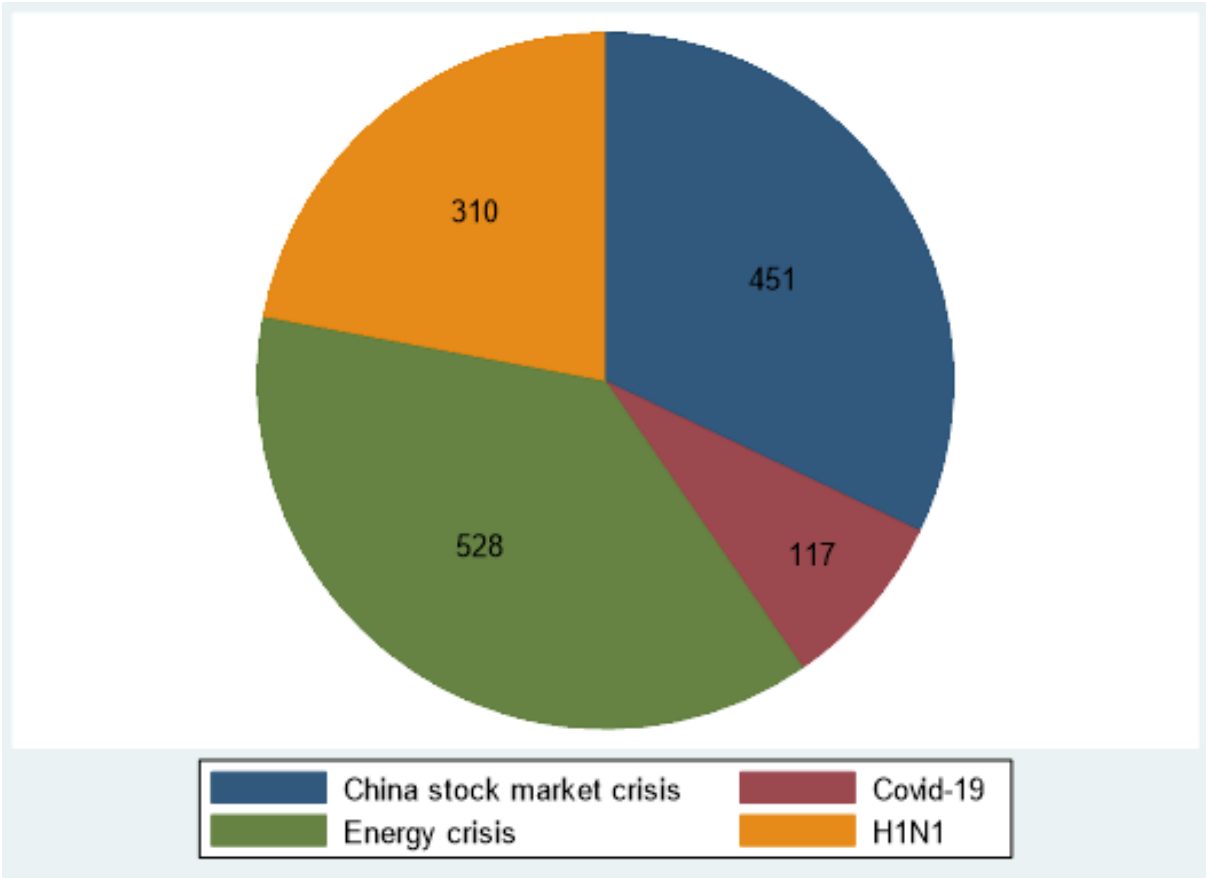


Figure 14: Number of negative shocks of the average performance of 29 companies during four sub periods



The results of the TGARCH (1,1) model in the second sample were different from the results in the first sample. All the coefficients from the second sample were negative, which indicates that high positive shocks increased the volatility more than negative shocks. Figures 15 and 16 presents that there were more positive shocks than negative shocks in each sub-period. Some of the returns were equal to 0, which means that the number of observations (see figures 15 and 16) was different than in the first sample (see figures 13 and 14). The percentage of positive shocks divided by the total number of shocks shows that there were slightly more positive shocks during pandemic shocks. Consequently, the sectors from the Dow Jones Industrial Average index reacted more to the pandemic shocks rather than other known shocks. Nevertheless, the results of both pandemic shocks were not significant. Therefore, it is impossible to answer whether the hypothesis for this sample is proved.

Figure 15: Number of positive shocks of the average performance of Dow Jones 30 companies during four sub periods

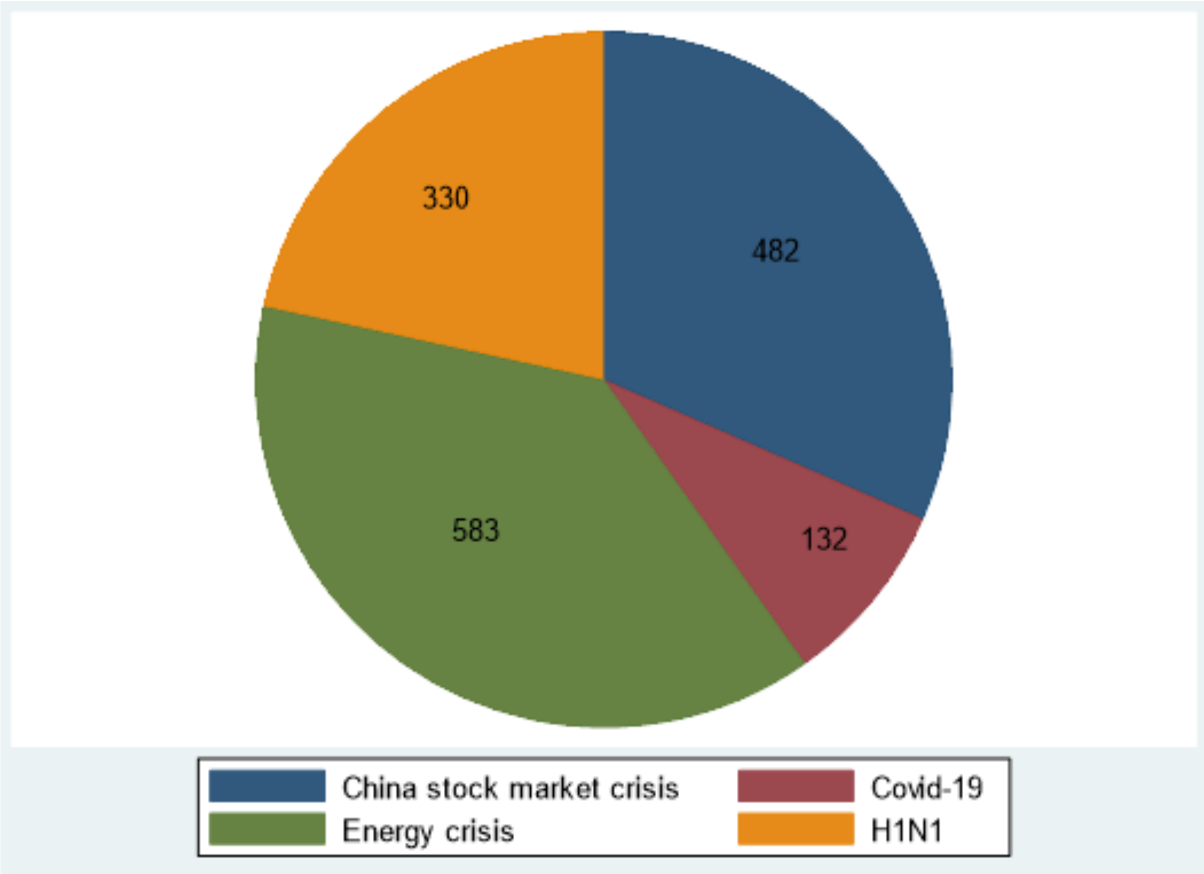
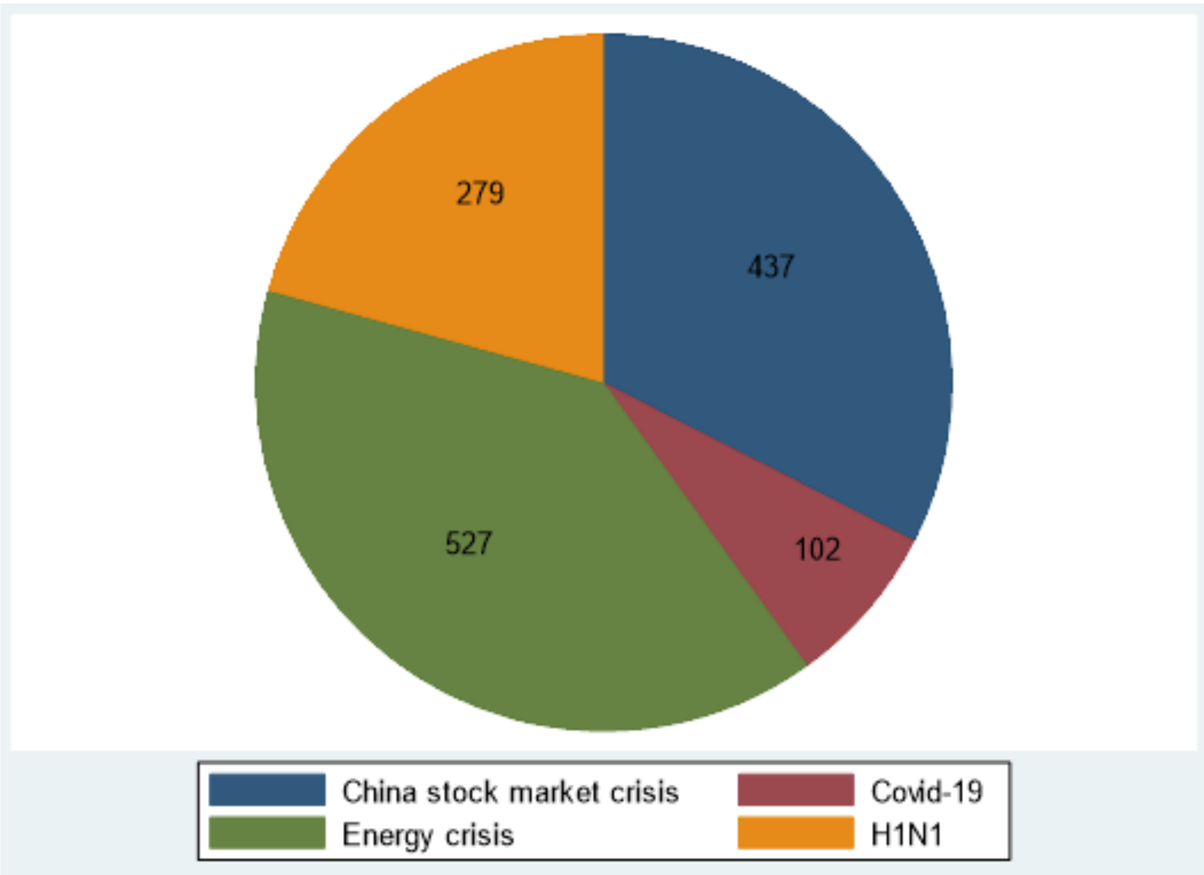


Figure 16: Number of negative shocks of the average performance of Dow Jones 30 companies during four sub periods



To summarize, the results in Tables 2 and 3 may provide the answer that the financial services sector reacts more to pandemic shocks rather than to other known shocks. In contrast, the results from the GARCH (1,1) and the TGARCH (1,1) models in the first sample state that the sub-periods which include other known shocks, generated volatility over a longer period (see tables 6 and 8). The results of the GARCH (1,1) and the TGARCH (1,1) model in the second sample were not unequivocal. The highest volatility in the GARCH model was observed during the energy crisis, however, the TGARCH (1,1) model showed that the COVID-19 outbreak was the most influential on the returns. To compare this result with empirical studies, Aloui and Jammazi (2010) suggested that a potential reason for the reduced impact of the oil shock on the market could be due to technology advancements. In contrast, the results in this study believes that the COVID-19 pandemic outbreak has such an influential role in the return due to technological advancement. As mentioned earlier, Baker et al. (2020) stated that COVID-19 outbreak is the one pandemic shock that has made a huge presence on the stock market from 1985. One potential reason could be due to technological advancement, where new information can quickly be spread out around the world and shaken many global investors with concerned and negative news. Therefore, looking at the sample of 29 companies from the financial services sector, it is possible to determine that the hypothesis of the research is correct after the conducted research. Nevertheless, the results of the second sample that consists of the other sectors are not as clear. The companies from the first sample are only from the financial services sector, however, the companies from the Dow Jones Industry index are from diverse sectors. Therefore, each company can react differently to the shocks. For instance, some sectors may not be as influenced by the performance of the Chinese Stock Market as the other sectors. Thus, the volatility observed during the China Stock Market crisis was lower than during the pandemic shocks or the energy crisis.

7.2 Limitations of the Interpretation

There is one fact about the outbreak of the H1N1 that should be taken into consideration when analyzing this sub-period. The pandemic occurred shortly after the financial crisis of 2007–2008. Since the length of the estimation windows in this research was 6 months, the end of the financial crisis was also included in the sample of this sub-period. This could have interfered with some results. In addition, the COVID-19 outbreak was also one of the causes of another event regarding the oil price war between Russia and Saudi Arabia (Bloomberg, 2020). These two incidents colliding with each other should be taken into consideration when interpreting the results of the period of the COVID-19 outbreak as well. Despite these limitations, the choices of pandemic shocks are still considered as good options due to proving its point to its huge impact on the stock market.

8. Conclusion

In the last chapter of this thesis, conclusion will be drawn. Firstly, the summary of the research will be presented. This will follow with suggestions on further research that could be found when the study was conducted.

8.1 Summary

The aim of this paper is to analyze how big of an impact the pandemic shocks have compared to other known shocks in the financial services sector in the stock market. The research question for this study is: Does the financial services sector react more or less severely to pandemic shocks compared to other known shocks? To answer this research question, three models, ARCH (1,1), GARCH (1,1), and TGARCH (1,1), were applied to estimate the volatility and the asymmetric volatility. The study conducted two samples of data. The first sample contained thirty financial services companies in North America that were active from 1st August 2002 to 8th May 2020. The second one consisted of thirty companies in the Dow Jones Industrial Average index. The samples were divided into four sub-periods that cover four widely known pandemic shocks and economic shocks known as the energy crisis, the H1N1 pandemic, China Stock Market crisis, and the COVID-19 pandemic outbreak.

Whilst Skata and White (1998) used the ARCH model to demonstrate their study, However, Awartani and Corradi (2005) could prove that the GARCH model outshined the ARCH model. Hence, the results from the GARCH model were only discussed between these two models in this study. The coefficients retrieved from the GARCH model in the first sample showed that other known shocks react more to the market. The energy crisis had the highest coefficients. Meanwhile, the coefficients of the China Stock Market crisis showed a higher value than the coefficients of the pandemic outbreaks. This finding could reflect upon Charles and Darne (2014) conclusion, that larger volatility shocks are principally due to events such as financial crisis and macroeconomic news. The result of this study showed that large changes in the volatility remained for a longer time in the future. Moreover, the results from the TGARCH model show that the coefficients during other known shocks are positive. Thus, negative shocks during the energy crisis and the China Stock Market crisis increased volatility more than positive shocks. This result agreed with the study from the U.S.–China Economic and Security Review Commission (2016;2017). In contrast, the results of pandemic shocks were the opposite. The outcomes present the behavioral asymmetry of the shock.

The results of the second sample were slightly different in the GARCH and the TGARCH model. The energy crisis shock was the most volatile in the GARCH model. However, the results during the China Stock Market crisis were not as volatile as in the first sample. Moreover, the results from the TGARCH model demonstrated that pandemic shocks responded more than the energy crisis or the China Stock Market crisis. This corresponded to Kang et al (2009) and Wei et al. (2010) that suggested nonlinear GARCH-class models (the TGARCH model) over linear GARCH-class models (the GARCH model). In addition, the result from our study regarding the influential role that the pandemic shocks have on the market further proved that technology advancement could be a potential reason for its increasingly bigger presence in the modern time (Baker et al., 2020; Aloui & Jammazi, 2010).

To conclude and to answer the research question of this study, the main findings of models indicate that the financial services sector responds less severely to pandemic shocks compared to other known shocks on the market. Nevertheless, the companies, included in the Dow Jones Industrial Average index, which are from various sectors were not so influenced by the shocks, such as the energy crisis or the China Stock Market crisis. As a result of this conclusion, the hypothesis of this paper is proven correct but only for the financial services sector.

8.2 Contributions & Further Research

This research emphasizes that there are currently limited studies on the relationship between the volatility of the stock returns and pandemic shocks in the two samples. Thus, this study contributes to new knowledge of pandemic shocks on the stock market. The study has been able to add new insights regarding theoretical models and relationships between the ARCH model and the GARCH models and the volatility of the pandemic shocks on the stock market in the financial services sector. Thus, with this study as a base, further research can be conducted regarding the pandemic shocks to the stock market. This will be beneficial to the literature and expand the knowledge of the topic.

Similar to Wei, Wang and Huang (2010) study, a further study can be conducted to further prove the evidence of our research with the use of a bigger sample, for instance, the number of companies that can be included in the sample. As of this study, the results from the first sample might not be representative of the entire financial services sector in North America. Moreover, the researchers can also choose to examine companies in other specific sectors in responding to pandemic shocks and/or economic shocks. Because each sector can react differently to pandemic shocks or economic shocks with a higher or lower impact.

As mentioned earlier, this research can be served as the basis for future studies. Therefore, it would be interesting to investigate other types of economic shocks, for instance, presidential elections, that might influence the stock returns. In this study, we decided to overlook the financial crisis 2007–2008 due to the collision with the H1N1 pandemic. This is also an event that would be interesting to look at and distinguish the impact of the financial crisis 2007–2008 compared to pandemic shocks.

Another suggestion of further research is that the research methodology may be extended to other GARCH models. An alternative model that could also be used in this study is the EGARCH (1,1) model. It provides results regarding the asymmetric volatility, similar to the TGARCH (1,1) model. Therefore, the comparison of these two models and how they fit the data during pandemic shocks and/or economic shocks would also be interesting to explore.

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Appendices

Appendix A - List of 29 companies from the financial services sector included in the first sample

Company name
INTL FCStone
Fidelity Investments
AllianceBernstein Holding LP
Geico
People's United Financial
New York Community Bank
Umpqua Holdings Corporation
Federal National Mortgage
Federal Home Loan Bank
Alliance Data Systems
Euronet
Raymond James
Credit Suisse
TD Ameritrade
Standard Bank Group
CME Group
UnitedHealth Group
Anthem
Principal Financial Group Inc.
Berkshire Hathaway
American International Group
Travelers
Farmers Group
Arch Capital Group
Crawford & Co.
USI
BlackRock
Icahn Enterprises
Annaly Capital Management

Appendix B - List of Dow Jones 30 companies in 2020

Company name	**Sector**
Microsoft	Information Technology
Apple	Information Technology
Visa	Information Technology
JP Morgan Chase & Co.	Financials
Johnson & Johnson	Health Care
Walmart	Consumer Staples
Procter & Gamble	Consumer Staples
Intel	Information Technology
UnitedHealth	Health Care
ExxonMobile	Energy
Home Depot	Consumer Discretionary
Disney	Communication Services
Coca-Cola	Consumer Staples
Verizon	Communication Services
Merch & Co.	Health Care
Pfizer	Health Care
Chevron	Energy
Cisco Systems	Information Technology
Boening	Industrials
McDonald's	Consumer Discretionary
Nike	Consumer Discretionary
IBM	Information Technology
United Technologies	Industrials
American Express	Financials
3M	Industrials
Goldman Sachs	Financials
Caterpillar	Industrials
Walgreens Boots Alliance	Consumer Staples
Dow	Materials
Travelers	Financials